Using Virtual Reality in the Structural Measurement of Plantation *Pinus Radiata*

by

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Declaration of Originality

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Candidate (70%) is the primary author. The candidate conducted the research, prepared the material for publication, and wrote the manuscript. Author 1 (15%) and Author 2 (15%) provided general guidance and editing as supervisors.

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Statement of Ethical Conduct

The research associated with this thesis abides by the international and Australian codes on human and animal experimentation, the guidelines by the Australian Government's Office of the Gene Technology Regulator and the rulings of the Safety, Ethics and Institutional Biosafety Committees of the University. Ethics reference number: H0017576.

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Abstract

Point cloud is a set of data points that is generally used for big data visualisation. Point cloud can render massive and complex data points in 3D space to represent objects or structures. Advanced user interfaces are widely integrated into modern computing devices enabling interaction between human and large data. Virtual Reality (VR) technologies have demonstrated their potential to provide virtual environment as a medium in exploration of large point cloud data, which is crucial in data analysis. VR technologies have showed positive results when integrated as training/simulation to some domains such as economic, military defence, and education. Integrating point cloud data into immersive VR could potentially support structural estimation of point cloud. This research focuses on the structural estimation of the point cloud data in VR using radiata pine plantation data. This research compares task performance between VR-point cloud assessment and field assessment, focusing on radiata pine plantation data. In addition to the task performance comparison, feedback about experience and impression of assessing radiata pine in VR-point cloud was collected from practitioners and analysed both quantitatively and qualitatively. Results from this research are useful to reveal the strengths and weaknesses of the VR-point cloud for structural estimation tasks in radiata pine trees.

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Chapter 1 Introduction

1.1 Background

Nowadays, visualisation methods are commonly used to assist with recognition of patterns or outliers in large datasets as well as to support data analysis. A recent study by (Chandler et al., 2015) introduced Immersive Analytics, which investigated how new interface technologies could be used to support analytical reasoning and decision making. Immersive analytics built on interface technologies such as touch surface, tabletop, immersive Virtual Reality/Augmented Reality (VR/AR) systems, and haptic and audio displays.

VR has been shown to lead to a better discovery in domains that primary dimensions are spatial, by providing a rich set of spatial and depth cues for complex structures visualisation. VR systems provide effective control of a virtual environment through 3D interaction techniques (Bowman et al., 2004). VR as a visualisation platform can be used to visualise a very large number of data points (point cloud) in various shapes, sizes, and colours, enabling users to do real time exploration inside the virtual environment (Donalek et al., 2014).

VR could potentially be helpful in providing an immersive environment especially for domains which have a challenging environment in the real world. For example, individual tree assessment in a forest, which can be challenging because there are many obstacles such as weather, terrain condition, and vegetation complexity (such as when climbing over fallen logs or moving through the undergrowth containing dense weed species). Individual tree comprises several different structures. Converting these structures into point clouds and visualise them in the VR environment could provide a safe environment for individual tree assessment.

1.2 Scope

There are a number of factors to be considered in terms of the suitability of visualising point cloud in VR for individual tree assessment, such as task performances in VR-point cloud and suggestions from forest practitioners about individual tree assessment in VR-point cloud. This research compared the task performance between VR-point cloud assessment and field assessment, as performed by forest practitioners. Additionally, feedback was sought from the forest practitioners about their experience and impression of assessing individual tree in VR-point cloud environment. In the end, strengths and weaknesses of the VR-point cloud environment for individual tree assessment were discussed.

1.3 Structure of This Thesis

This section briefly describes structure of this thesis in a following way:

Chapter 2 summarises literature review from relevant research fields including overview of data visualisation, visual analytics, Virtual Reality (VR) technology, point cloud visualisation in VR, and individual tree assessment in forest inventory, as well as briefly describes research gap among those fields.

Chapter 3 explains research goals, research contributions, research questions, and high-level overview of research methodology.

Chapter 4 describes data collection for this research as well as briefly explains methods for data analyses in this research.

Chapter 5 discusses results and data analyses.

Chapter 6 explains discussion from the results and data analyses. The discussion explicitly answers the research questions. Besides, this chapter also outlines some key limitations from this research as well as draws conclusion from this research.

References used in this thesis are listed in the References part.

Chapter 2 Literature Review

2.1 Data Visualisation Overview

Since the late 20th century, statistical computing started to be developed, which could accommodate large datasets (Kehrer et al., 2012). Computer capacity and processing speed increased rapidly since large-scale statistical and graphics computing was invented (Friendly, 2008). High-dimensional data appear in several fields such as biology, physics, or chemistry. For example, genomic microarrays in biology as researched by (Clarke et al., 2008), spectrometry data in air quality research in physics as researched by (Engel et al., 2012), and chemical compositions in combustion simulations in chemistry as researched by (Gerber et al., 2010). Scientific data simulation often contains high-dimensional data. The scientific data visualisation might comprise dense 3D spatial data structures, as illustrated in Figure 1. Dense 3D spatial data are fundamental for geographical information system (GIS) which consists of several components such as spatial, graphical, numerical, and textual components (Abdul-Rahman and Pilouk, 2007). In GIS, 3D spatial data are represented in the form of points, lines, surface, relief, and volume (Schneider and Weinrich, 2004).

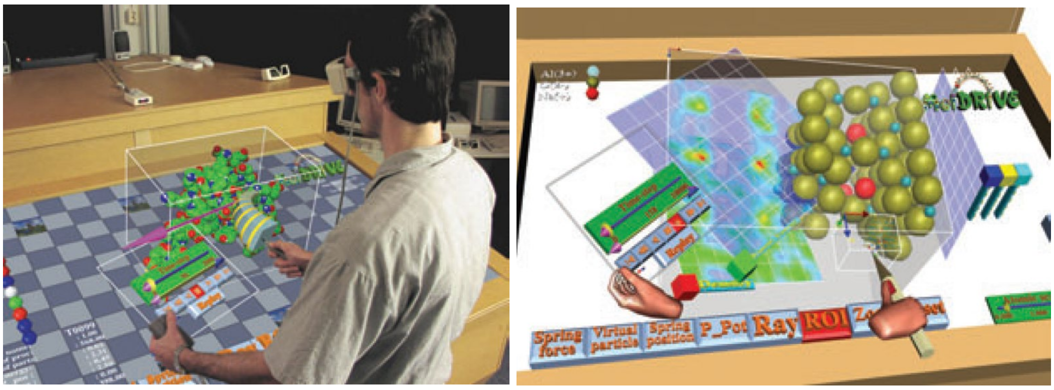


Figure 1: Early work of scientific visualisation in Virtual Reality (VR); (Left) MolDRIVE: particle steering of protein fragment with the spring manipulator on the RWB; (Right) Visualisation Client of MolDRIVE: time-control widget on the Plexipad (taken from: (Koutek, 2003)).

Previous works with 3D spatial data visualisation have explored data from various technologies, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), confocal microscopy, and ultrasound. These technologies were used to analyse scientific data in several domains, such as medicine, biology, astronomy, palaeontology, geography, archaeology, and engineering (Kaufman and Mueller, 2005). Previous work by (Peng et al., 2010) introduced the V3D visualisation engine, which provided cross-platform and real time 3D visualisation of gigabyte-sized microscopic image stacks. V3D visualisation rendered heterogeneous data, such as volumetric image data and various 3D surface objects. However, high dimensional data represent a challenge when visualising interesting structures that may exist in the data (Donalek et al., 2014). The challenge occurs when some of the interesting structures are in a low-dimensional projection. Those interesting structures in the low-dimensional projection may fade out, leaving part of the high-dimensional data to be unrecognisable.

2.2 Visual Analytics Overview[1]

Incorporating data analytics and visualisation is the core of visual analytics (Keim et al., 2008). Visual analytics is described as "the science of analytical reasoning facilitated by interactive visual interfaces" (Thomas and Cook, 2006). It focuses on handling massive, heterogeneous, and dynamic data along with human judgement by intuitive visualisation and interaction techniques (Keim et al., 2006); (Shen et al., 2012). As shown in Figure 2 and 3, visual analytics' scope contains several interdisciplinary research areas including visualisation, cognitive and perceptual science, interaction, data mining, and statistics (Keim et al., 2006). Visual analytics integrates scientific and information visualisation with four disciplines: data mining, data management, human-computer interaction, human perception, and cognition. It takes advantages of computational power and human's cognitive ability, to enable analyses of data at both broad and fine levels to gain insight and knowledge for decision-making process (Elgendy and Elragal, 2014). These observations are illustrated in the model by (Van Wijk, 2005), as shown in Figure 4. Computers have the ability for statistical analysis of complex data, data modelling and data visualisation, while humans possess the ability of visual perception and cognition (see Figure 5 and 6). Visualisation bridges the computer and human for data analysis. In summary, visual analytics combines human cognition, visualisation, and data analysis.

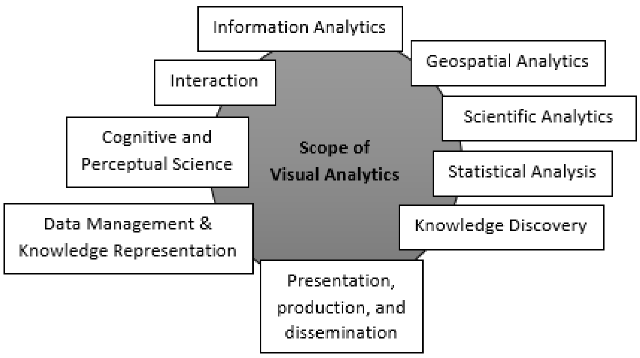


Figure 2: Interdisciplinary research areas of visual analytics (taken from: (Keim et al., 2006)).

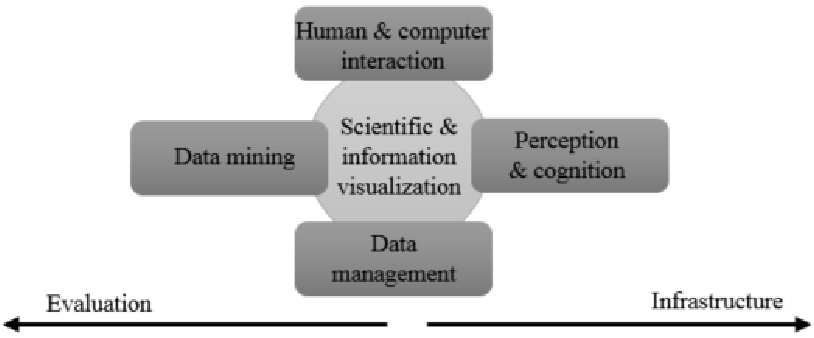


Figure 3: Visual analytics integrates scientific and information visualisation with core adjacent disciplines: data management and analysis, spatio-temporal data, and human perception and cognition. Successful visual analytics research depends on the availability of appropriate infrastructure and evaluation facilities (taken from: (Keim et al., 2008)).

[1] Some parts of this section have been published in Paper 1 (see "Statement of Authorship" page iii).

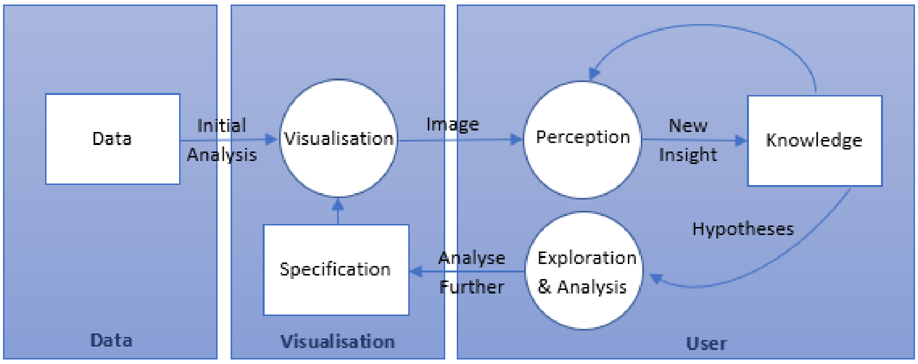


Figure 4: Simple model of visual analytics by (Van Wijk, 2005).

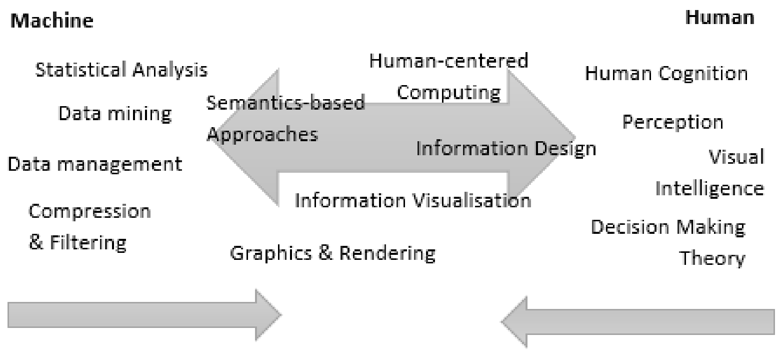


Figure 5: Visual analytics integrates scientific disciplines to improve the divisions of labour between human and machine (taken from: (Keim et al., 2008)).

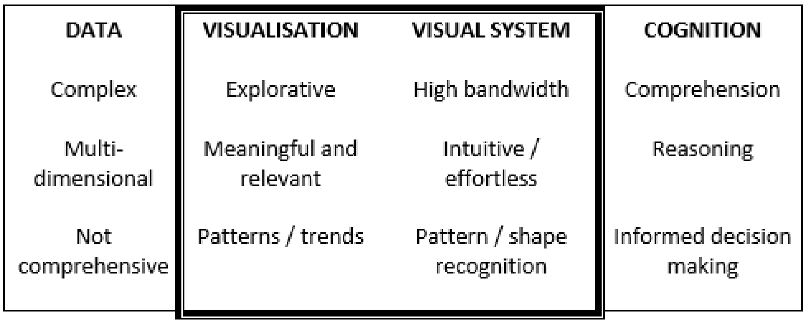


Figure 6: Visual Human-Data Interface - visualisation is the bridge between data and human visual system for data analysis (taken from: (CSIRO, 2017)).

Visual analytics is a natural fit for Big Data since it can scale its visualisations to represent thousands or millions of data points, unlike standard pie, bar, and line charts. Moreover, it can handle diverse data types as well as present analytical data structures that are not conveniently displayed onto a computer screen, such as hierarchical and neural sets (Elgendy and Elragal, 2014). Successful examples of existing visual analytics tools include (Tableau, 2020), (Spotfire, 2020), and ADVIZOR developed by (Advizor Solutions, 2020). These tools show the possibility and advantage of transferring advanced visualisation techniques developed by researchers into commercial software products (Zhang et al., 2012).

Previous work by (Keim et al., 2008) discussed several key requirements of visual analytics. Firstly, data visualisation should be able to scale with the size and dimensionality of the data space. Secondly, it should support multiple levels of detail with sufficient quality to avoid uncertainty and misinterpretation. Lastly, visual analytics system should be supported by advanced display devices that can work on levels needed for analysis and interaction technique(s) that allow human to interact directly with the visualised datasets such as filtering, zooming, or linking for data exploration (Keim, 2001). Different display devices and methods of visualisation can also present challenging interaction techniques, depending on the devices and visualisation design.

Recent work on immersive analytics discussed how large scale display technologies could be used to support analytical reasoning and decision making (Chandler et al., 2015). Chandler's work also extended to other states of the art technologies such as touch surface, tabletop, immersive VR/AR system, and haptic and audio displays. While immersion alone may already have a beneficial effect on the perception and comprehension of large data sets, effective interaction with immersive systems such as VR needs to be well understood to fully leverage the additional degrees of freedom that such systems provide for manipulating data.

2.3 Virtual Reality (VR) Overview[2]

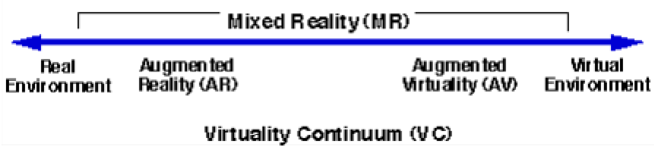


Figure 7: Simplified representation of a virtuality continuum (taken from: (Milgram and Kishino, 1994)).

The concept of "virtuality continuum" is related to the combination of classes of objects presented in particular situations, as illustrated in Figure 7, where the real environment is shown at one end of the continuum and the virtual environment shown at the other end of the continuum. A real environment defines environments that consist of real physical objects. It includes what is observed via a conventional video display of a real-world scene. For example, direct viewing of the same real scene, but not via any particular electronic display system. A virtual environment defines environments which consist of virtual objects, for example a conventional computer graphic simulation.

VR integrates computer and human-computer interfaces to create a 3D world effect, which contains interactive virtual objects with a strong sense of 3D presence (Bryson, 1996). VR came to the public's attention in the late 1980s. Jaron Lanier was a pioneer computer scientist who introduced the term 'virtual reality' in 1987. The effect of VR is attained through several components (Bryson, 1996):

- "A head-tracked, usually stereoscopic, display that presents the virtual world from the user's current head position, including the visual cues required so the virtual scene is perceived as independent of the user, which produces a sense of immersion.";
- "A high-performance computer graphics system that computes and renders the virtual world.";
- "Three-dimensional input devices that allow the user to provide input to the system directly in three dimensions."

VR was firstly attempted by a cinematographer named Morton Heilig in 1950s. (Heilig, 1962) created Sensorama: an arcade-style theatre cabinet which could stimulate the senses and was intended to fully immerse individuals in the film. Sensorama comprised stereo speakers, fans, a stereoscopic 3D display, smell generators, and a vibrating chair.

Many studies have implemented different interaction techniques within 3D environment, such as using hand tracking as developed by (Bryson, 1992), gaze as developed by (Pfeiffer, 2008), go-go arm extension technique as developed by (Poupyrev et al., 1996), ray casting technique as developed by (Duval et al., 2008), spring-based technique as developed by (Koutek and Post, 2001), human body as developed by (Roupé et al., 2014), and gestures as developed by (Lévesque et al., 2011). Previous work by (Arms et al., 1999) mentioned that interaction techniques could be done more easily and quickly in a 3D environment compared to a desktop system. However, the users might feel intimidated by immersive 3D environment encountered as a new technology which made them unsure and more careful of their interaction and which therefore affected the system performance. There is no single optimal way to interact within a 3D environment because each pattern or technique has strengths and weaknesses depending on application goals and the intended audience (Jerald, 2016). For example, the go-go technique works well when ease of reach is important but is usually not appropriate when training for real world tasks.

[2] Some parts of this section have been published in Paper 1 (see "Statement of Authorship" page iii).

The concept of immersive VR gives users the psycho-physical experience of being surrounded by a virtual environment. In a VR system, physical immersion is a property of the VR system that replaces or augments the stimulus to the participant's senses (Coomans and Timmermans, 1997). Immersive VR has potential in many application areas, for example, visual prototyping for design mock-up as developed by (Balaguer and Gennaro, 1996), simulators and training of Landing Signal Officers as developed by (Greunke and Sadagic, 2016), improving teaching experience in education through VReX platform as developed by (Ying et al., 2017), low-cost automated driving simulator as developed by (Schroeter and Gerber, 2018), surgical simulation to improve Operating Room performance as developed by (Seymour et al., 2002), and telepresence for remote collaboration (Edwards, 2011); (Riva et al., 2003). In the case of 3D spatial data sets, three components of immersion (head tracking, field of regard, and stereoscopic rendering) have some benefits where each component has variable influence on different task conditions (Laha and Bowman, 2012). For instance, head tracking with high field of regard was found to be an advantage for spatial search tasks, because this combination allowed users to walk around the dataset physically. VR interfaces allow intuitive exploration of 3D volumetric data for spatial search tasks by inspecting the data from various angles and positions (Koutek, 2003). This would provide better discovery for domains whose dimensions are spatial because VR can display 3D spatial data as well as provide depth cues in the visualisation.

VR is also capable of providing a sense of presence, feeling of 'being there', of objects and human at the same environment. Presence is defined as a subjective phenomenon that results from experiences induced by immersive VR (Slater and Wilbur, 1997). Previous work by (Sanchez-Vives and Slater, 2005) argued that presence is defined as consciousness in VR because every aspect of consciousness (the sense when perceiving a given stimulus, the sense of owning the stimulus, and the sense of acting on the stimulus) occurs when the individual is immersed in VR.

VR also aids spatial awareness. Previous research has been shown that VR could improve spatial skills of physically disabled children after intensive exploration inside complex virtual environments (Stanton et al., 1996). VR for spatial awareness is also an advantage for usage such as in exhibition room or museum environment, where human are not familiar with physical space (Almutawa and Ueoka, 2019).

Another key factor to an interactive VR experience is the feedback or sensory feedback (Coomans and Timmermans, 1997); (Sherman and Craig, 2002). Unlike more traditional media, VR systems provide direct sensory feedback to human based on their physical position. Tracking operations of the sensor must be done without a significant delay; therefore it requires the use of a high-speed computer as a mediating device. The feedback can be in several forms such as touch or haptic feedback as developed by (Achibet et al., 2015), electro-tactile feedback as developed by (Hummel et al., 2016), visual feedback or even olfactory feedback. In order to link the sensory feedback of the VR system on the position of the human, the VR system must track the human movement whether by head tracking, hand tracking, or major body joints (Sherman and Craig, 2002).

Building interactive visual interfaces for VR is nowadays strongly supported through software and hardware platforms such as using Unity3D from (Unity Technologies, 2020) for modelling, Oculus Rift from (Facebook Technologies, 2020) or HTC Vive from (HTC Corporation, 2020) as immersive displays, and Oculus/Vive hand controllers or (Leap Motion, 2020) for interaction in the VR (Donalek et al., 2014). Other examples include Second Life from (Linden Lab, 2020) and its open-source counterparts that use the Open Sim / (Open Simulator, 2020) platform.

2.3.1 Interaction in an Immersive VR Environment

Interaction in an immersive VR environment is required in cases where the data become very dense or when the tasks require a lot of exploration. Interaction in an immersive VR environment includes placement of cutting planes for manipulation as developed by (Cowperthwaite et al., 1996)) and (Prouzeau et al., 2019), structure-aware selection technique as developed by (Yu et al., 2015), viewpoint control for navigation or exploration as developed by (Bolwerk, 2017), indirect control panels as developed by (Zhang and Meruvia-Pastor, 2017), or compound interaction such as combining selection and manipulation techniques as developed by (Bowman and Hodges, 1997). Due to its higher spatial dimension, interaction with the virtual object may require higher degrees of freedom for viewing and manipulation.

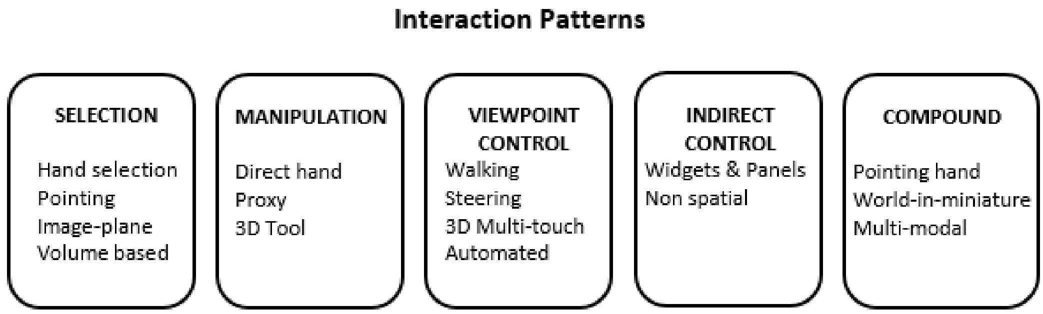


Figure 8: Five high-level interaction patterns including interaction techniques as introduced by (Jerald, 2016).

Previous work by (Jerald, 2016) outlined five high-level of interaction patterns in immersive VR environment that were further divided into several interaction techniques, as illustrated in Figure 8. Selection denoted a beginning of a manipulation task, especially when a virtual object was located at a distance from the human viewpoint. Manipulation came after selection to modify the selected virtual object. Viewpoint control was a subset of manipulation where it modified the virtual object's perspective and might include translation, orientation, and scaling. However, some implementations of viewpoint control might cause motion sickness. Indirect control provided control through a medium to modify the virtual object or 3D environment. Compound combined one of each of the previous four interaction patterns, and therefore it could be chosen which technique was good for selection, manipulation, and viewpoint control.

Immersion, such as in VR, could fill the gap between human perception and interaction space. Researchers investigating the effects of immersive VR environments have run empirical studies further demonstrating significant benefits of an immersive environment for visualisation and exploration of volume-rendered confocal microscopy datasets (Forsberg et al., 2008); (Zhang et al., 2003); (Zhang et al., 2001). Immersive VR environments have been used to visualise 3D object such as in 3D network visualisation as written by (Cordeil et al., 2017) or in scientific visualisation as written by (Koutek, 2003)). Such immersive VR environments may reveal spatially complex structures that are easier to explore and analyse when compare with traditional non-immersive environments such as a desktop environment (Laha et al., 2014).

Interaction in immersive VR environment is made difficult by the fact that real world objects (e.g. human hands) either need to be re-modelled as completely virtual hand or shown as video-overlays (Etemadpour et al., 2013); (Metzger, 1993); (Yokokohji et al., 1996). However, Oculus Rift has introduced Touch controllers (right-hand and left-hand controllers) and their newer version enables human hands to be overlaid virtually in VR. Several interaction techniques can be implemented in VR separately or compounding to create an optimal interaction technique(s). Depending on the purpose of the interaction, some interaction technique(s) may perform better than others when using rift touch controllers.

2.3.2 Data Exploration in an Immersive VR Environment

As discussed briefly in Section 2.1, VR provides an interactive interface which can accommodate large 3D spatial data, enabling users to do real time data exploration or data analysis (Section 2.2). iViz is one example of *OpenSim*-based large data visualisation in VR environment which can visualise millions of data points in various shapes and colours, and also enable collaborative multi-user data exploration (Donalek et al., 2014). Immersive analytics was developed later as emerging research investigating how technologies could be used to support data analysis and decision making (Section 2.2).

Previous work by (Batch et al., 2019) presented an evaluation of performance, presence, and space use with domain experts. Unexpectedly, their finding indicated that some participants did not maximise the use of the fully immersive VR environment for the analysis since they mostly stayed in place when analysing the data. Batch et al.'s research, however, generated participants' interest in further development of domain-specific immersive analytics in their case in the economic domain. One of the reasons was because of the high presence and engagement level in an immersive environment, as well as the natural interaction technique that supported participants in quickly exploring their data. Batch et al.'s findings highlighted the importance of interaction techniques or mechanisms in addition to visualisation to support the analysis performance. The different tasks required different interaction mechanisms and in the case of immersive VR environment, the 6DOF input devices may be more beneficial than 2DOF input in data exploration.

2.4 3D User Interface for VR

2.4.1 Output Devices

Visual displays are the most common output devices. For VR, visual displays can be in the form of fully-immersive displays and semi-immersive displays (Bowman et al., 2004). Fully immersive displays allow the human to be fully immersed within a VR environment. All real-world objects are represented with virtual objects inside the VR environment. Fully-immersive displays include head-mounted displays (HMDs). Semi-immersive displays allow the human to see virtual objects and VR environment, with human being outside of the VR environment. Semi-immersive displays include monitors, workbenches, and surround screen VR systems. Visual displays have pros and cons, some of them were summarised by Bowman as in Table 1.

Table 1: Visual display devices pros and cons (taken from: (Bowman et al., 2004)).

Visual Display Types	Pros	Cons
Monitors	○ Relatively expensive ○ Very high spatial resolution ○ Can use virtually any input devices	○ Small FOV ○ Not very immersive ○ Virtual object occlusion problem
Surround-screen displays	○ Large FOV ○ Virtual objects easily mixed in 3D application	○ Requires wide physical space ○ Expensive device ○ Virtual object occlusion problem
Head-mounted displays	○ 360-degree FOV ○ Portable device ○ No virtual object occlusion problems	○ Small FOV ○ Lower spatial resolution than projection-based devices ○ Ergonomic issues due to weight and fit of device

Besides visual displays, there are other output devices such as auditory displays, haptic displays, and tactile displays. These displays are often used as feedback when interacting with virtual objects. For example, auditory displays can generate sound which enables people with visual impairments to navigate in VR (Zhao et al., 2018). Auditory displays are also useful for collaborative interfaces where there are several humans collaborate to each other inside virtual environment (Nguyen et al., 2017). Haptic and tactile displays allow human to touch and feel within the virtual environment. These are useful especially for interacting with the virtual objects.

2.4.2 Input Devices

Input devices are physical tools, which are used to implement interaction techniques. Previous work by (Anthes et al., 2016) has created a taxonomy of input devices divided into controllers and tracking, as shown in Figure 9. Controllers include Oculus rift's Touch controllers from (Facebook Technologies, 2020) and HTC Vive's controllers from (HTC Corporation, 2020). Tracking is divided into two categories: body and hand. Body tracking includes PrioVR from (Yost Labs, 2020) and Manus from (Manus VR, 2020). Hand tracking is further divided into contact-free, wrist, and glove or finger. Contact-free hand tracking includes (Leap Motion, 2020), wrist hand tracking includes FingerTrak from (Cornell SciFi Lab, 2020), while glove or finger hand tracking includes SensorialXR from (Neuro Digital, 2020) and Manus from (Manus VR, 2020).

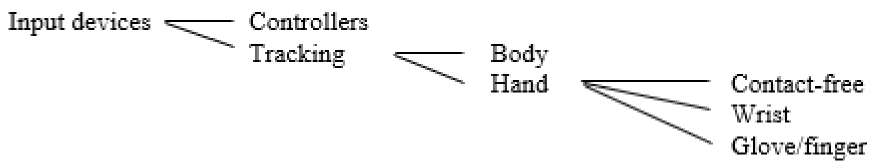


Figure 9: Taxonomy of input devices (taken from: (Anthes et al., 2016)).

Previous work by (Lin et al., 2017) has implemented hand touch and hand gesture as input methods for the 3D user interface in VR. However, these input methods are generally for universal tasks such as selection and manipulation. Domain-specific tasks such as scientific visualisation should have a specific design of the VR environment as well as scalable interaction techniques to be able to optimise the tasks of inspecting both perceptual (colour, size, shape, texture, transparency) and abstract (numerical, description, statistical) data (Koutek, 2003).

Oculus Rift's Touch controllers are one of the commonly used input devices for VR (Oculus Rift, 2020). Touch controllers have 6DOFs which allow tracking of the controller's position, orientation, as well as gestures (such as thumbs up) in the VR environment. Touch controllers display virtual hands in VR which overlays on top of the physical hands, using a real time hand tracking.

2.5 Point Cloud Visualisation in Immersive VR Environment

Point clouds are one of the visualisation models inside a 3D space. Point clouds may contain points of different types and sizes, individual points of interest, and areas of different densities, clusters, and outliers (Bach et al., 2017). Point clouds are also used for big data visualisation as they can render massive and complex data points in 3D space to assist the discovery of interesting patterns or outliers. For example, iViz, developed by (Donalek et al., 2014), is a practical big data visualisation tool that uses point cloud with an interactive interface.

Visualisation research employing immersive VR environments has focused on large immersion displays (such as CAVE) and Head-Mounted Displays (HMDs). Immersive VR environments have been proven to be effective in several scientific applications such as TeleArch for collaborative virtual archaeology simulation developed by (Kurillo and Forte, 2012), geographic information system using CAVE-type system developed by (Bennett et al., 2014), geoscience visualisation using HMD developed by (Helbig et al., 2014), stream lines and particle visualisation in physics using HMD developed by (Kageyama et al., 2000), or DT-MRI visualisation in medical science using CAVE developed by (Zhang et al., 2001). Based on their scientific applications, stereoscopy and head tracking can clearly improve user performance. Previous work by (Raja et al., 2004) evaluated 3D scatterplot visualisations in a CAVE environment for individual users. Raja et al. research suggested that higher degrees of physical immersion allowed fewer errors and shorter completion time to solve the tasks. They also found out that head tracking might reduce disorientation when enabled. Similarly, in the case of HMD, recent work by (Wagner Filho et al., 2018) found an improved task performance in HMD-based environment as compared with desktop-based 2D or desktop-based 3D environment for analytical tasks of dimensionally-reduced 3D scatterplots, in terms of effort, navigation, and subjective perception of accuracy and engagement. The analytical tasks were related to perception of different distances: near, medium, and far. The perception errors were similarly low for both desktop-based and HMD-based environments.

Previous work by (Yu et al., 2015) suggested some selection techniques for interaction with point cloud data in virtual exploratory data analysis. One of the preferable techniques from their experiment was using PointCast selection, which treated the whole point cloud environment as individual points and used picking or ray pointing metaphor known from traditional 3D selection as a projection to select/mark each point. However, their apparatus was a Microsoft Surface Pro 2 with direct touch or pen input, rather than incorporating HMD in immersive VR environments. (Yu et al., 2012) presented two techniques for spatial-aware data selection, specifically for subsets of large 3D point cloud datasets, using 2DOF interaction either with mouse or with direct touch input. They suggested using CloudLasso tool to select subsets of large 3D point cloud datasets. A few years later after Yu et al. publication, (Chen et al., 2019) introduced LassoNet technique which provided more advanced subsets of 3D point cloud datasets selection as compared to CloudLasso using deep learning. Previous work by (Keim, 2000) outlined that 3D scatterplot suffered from well-known issues such as perception and over-plotting which prevent users from properly perceiving the data. However, incorporating VR into the design could provide navigation and natural interaction with the head and hand tracking. Recent work by (Prouzeau et al., 2019) found that the performance in low density was worse than in high density using cutting plane technique, and consistently good accuracy across all densities using density-based haptic vibration technique. Prouzeau et al. experiment showed that some participants took advantage of VR when solving the tasks. For example, intersecting their head the point cloud spheres feature, walking around, and moving their head to solve the task. As future work, Prouzeau et al. were interested in finding relevant spatial features in 3D scatterplots by exploring other 3D volume generation techniques.

2.6 Individual Tree Assessment in Forest Inventory

Light Detection and Ranging (LiDAR) technology has been used to scan forest attributes, such as canopy height, sub-canopy topography, and vertical distributions of canopies, as it can retrieve horizontal and vertical information at high spatial resolutions and vertical accuracies (Lim et al., 2003). LiDAR can provide a dense cloud of millions of 3D points and each point combines to create a rich 3D model of the target object or area. With recent advances in Unmanned Aerial Vehicle (UAV) remote sensing technologies, a possibility to obtain tree height semi-automatically has become a reality. However, in terms of height accuracy, (Krause et al., 2019) indicated that the Root Mean Square Error (RMSE) of UAV was still slightly higher than current field measurement practice with values of 0.304 m for UAV and 0.34 m for field measurement. Similarly, (Tian et al., 2019) combined Terrestrial Laser Scanner (TLS) with the UAV image-based point cloud. The UAV image-based point cloud was generated from the technical reconstruction of 2D aerial images and was registered to the TLS point cloud data. The accuracy (RMSE) of the TLS registration reached 6 cm, which shows that the combination of TLS and UAV can be used widely in the forestry research. Thus, forestry research can adapt the current technology for forest inventory purposes.

Radiata pine (*Pinus radiata*) is a major plantation species grown around the world and is the species with the largest area of plantation in Australia (ABARES, 2018). This species is used for commercial timber production and provides most of the volume of logs harvested annually in Australia (Forest Products Commission, 2020). Radiata pine is widely used for house framing, furniture, and in construction such as for posts, retaining walls, and mining timber. Forest inventory methods are used to estimate the total volume of wood in Radiata pine plantations and estimate the variety of timber products that can be extracted from the plantation. This data is critical to a forest company planning their forest harvesting and forest product sales.

Forest inventory guidelines specify what forest data must be collected in the field (CNI Regional, 2007). The collected data for forest inventory include tree diameter, tree height, and tree quality assessment. Tree diameter is measured in millimetre units at a distance of 1.3 m above the ground. Tree height is measured in metre units, to the top of each measured tree. Tree quality assessment is a structural estimation on the stem and includes for each tree a description of branching, sweep, and additional specific features such as stem damage and spiked knots. Tree quality assessments are classified into different codes provided by the forest inventory guidelines to indicate the estimated structure size/condition. The classification is done manually by inventory forester observing the stem from the ground. Inventory foresters are forest practitioners who have different expertise, such as crew leader, Second-in-Charge (2IC), auditor, or consulting.

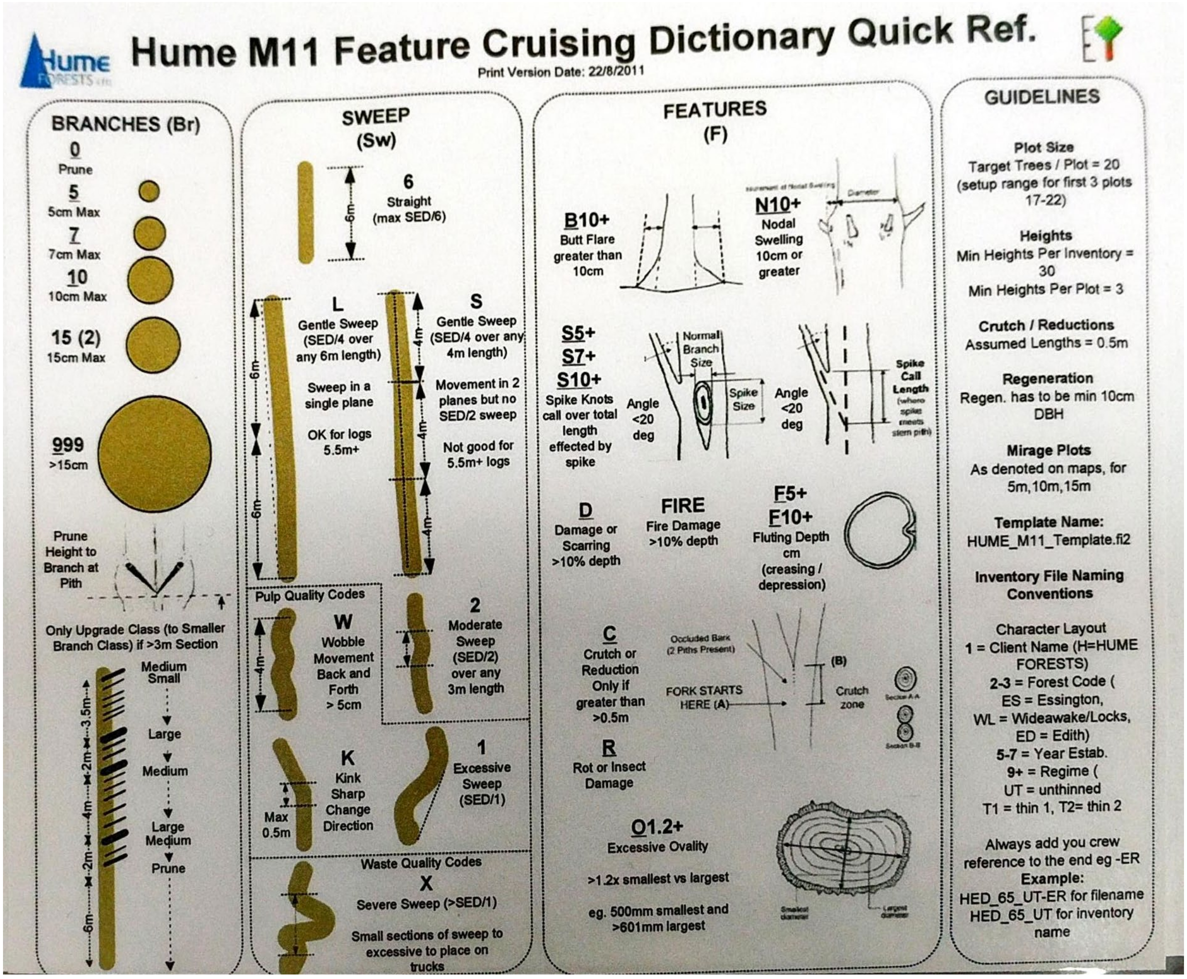


Figure 10: Reference card for tree quality assessment. Copyright 2020 by Interpine Group Ltd.

Table 2: Tree quality assessment codes and description from forest inventory (CNI Regional, 2007).

Tree quality assessment	Code	Description	Quality/ Structural Code
Branch	0	Prune	Quality code
	5	5 cm (maximum branch diameter size)	
	7	7 cm (maximum branch diameter size)	
	10	10 cm (maximum branch diameter size)	
	15	15 cm (maximum branch diameter size)	
	999	>15 cm (maximum branch diameter size)	
Sweep	6	Straight stem	Quality code
	L	Gentle sweep (SED/4 over any 6 m length)	
	S	Gentle sweep (SED/4 over any 4 m length)	
	2	Moderate sweep (SED/2 over any 3 m length)	
	1	Excessive sweep (SED/1)	Structural code
	K	Kink – Sharp change direction (deviation) of the stem	
	W	Wobble – Two or more deviations occur on the stem (> 5 cm length)	
	X	Severe sweep (> SED/1)	
Features	D	Damage to the stem (holes, thinning or scars, snow damage)	Quality code
	S5+	Spike knot 5 cm in length (maximum) and < 20 degrees	
	S7+	Spike knot 7 cm in length (maximum) and < 20 degrees	
	S10+	Spike knot 10 cm in length (maximum) and < 20 degrees	
	B10+	Butt flare (> 10 cm)	
	N10+	Nodal swelling (> 10 cm)	
	F5+	Fluting (depth > 5 cm)	
	F10+	Fluting (depth > 10 cm)	
	R	Rotten tree or insect damage	
	O1.2+	Ovality > 1.2x (smallest vs. largest)	

Figure 10 shows a reference card used for tree quality assessment. Forest practitioners refer to this reference card when collecting the tree quality assessment data in the forest. The reference card comprises different codes for each tree quality assessment. The meaning of each code is shown in Table 2.

- Branch is assessed outside the bark. There are several codes for branch. Each code represents the maximum branch diameter size. The sizes can vary with types of forests or trees and maturity of plantation plots.
- Sweep is the curvature of the stem being assessed, from a straight line placed along the inside edges of sweep. Sweep assessment is proportional to the Small End Diameter (SED) of the length over which it is assessed. When applying a sweep code, the assessment of length (for example 4 m) must be applicable for the entire length of the sweep code and any adjacent higher coded feature lengths. For example, it must be possible to fit up to a 4 m log with SED/4 anywhere throughout an 'S' code (short – gentle sweep of SED/4 over any 4 m length), and any adjacent 'L' code (long – gentle sweep of SED/4 over any 6 m length) or '6' code (straight stem).
- Under the category 'features':
    - Damage is damage to the stem, which included holes, pulled/broken out branches, stem reduction, thinning damage or scars, and snow damage. If there is any evidence of rotten stem due to insect damage, they should be classified as 'R' (rotten tree).
    - Spike knots are the result of acutely angled branches (angle < 20 degrees) with size was recorded as the length of the hard knot cut along the stem.

- Butt flare is a sudden increase in diameter at the base of the tree.
- Nodal swelling is a swelling stem that occurs around a branch node.
- Fluting is a depression to the circumference of the log due to creasing of the bark.
- Ovality of a stem is the variation between the shortest and the longest diameter axis through the centre of the stem.

After data collection in the field, the tree assessment data are audited to ensure that the inventory was carried out efficiently and accurately. The tree assessment data are audited at the plot level with the quality of the plot inventory measurements graded by the auditor using an established plot grading system. There are standards and tolerances allowed for a range of inventory features. Demerits are incurred if the assessment data do not meet specified standards, for example when quality codes are wrongly used. The demerit is determined according to each collected data inventory (CNI Regional, 2007):

- Height (maximum 15 demerits per tree)
  - Trees < 20 m have a tolerance of ± 0.5 m then incur 3 demerits per 0.5 m difference.
  - Trees 20-30 m have a tolerance of ± 1.0 m then incur 2 demerits per 0.5 m difference.
  - Trees 30-40 m have a tolerance of ± 1.5 m then incur 0.5 demerits per 0.5 m difference.
- Diameter (maximum 15 demerits per tree)
  - Trees with diameter < 500 mm have a tolerance of ± 5 mm then incur 1 demerit per 1 mm.
  - Trees with diameter > 500 mm have a tolerance of ± 10 mm then incur 1 demerit per 1 mm.
- Tree quality assessment (including branch, sweep, and feature)
  - At heights < 12 m, quality code errors incur 3 demerits and structural code errors incur 6 demerits.
  - At heights from 12 m to 20 m, quality code errors incur 2 demerits and structural code errors incur 4 demerits.
  - At heights > 20 m, quality code errors incur 1 demerit and structural code errors incur 2 demerits.

High demerit scores mean the assessment is less reliable. Forest practitioners are required to achieve high standards when assessing each sampled tree in the plantation. Achieving high standards in the assessment remains difficult because tree assessment in a forest is challenging. There are many obstacles such as weather, terrain condition, and vegetation complexity (such as when climbing over fallen logs or moving through the undergrowth – which often contains dense weed species).

2.7 Summary (Research Gap)

Visualisation methods are commonly used to assist with recognition of patterns or outliers in large datasets. Visualisation methods are also used to support data analysis. This is where the domain of visual analytics comes from, integrating data analytics with visualisation (Keim et al., 2008). Recent visualisation technologies are capable of providing human interaction within the data analysis. Technologies such as immersive VR/AR environment, large touch surfaces, or sensor devices are used as user interface for data analysis (Chandler, 2015).

VR offers an immersive environment as a medium for scientific visualisation. An immersive VR environment can reveal spatially complex structures that are easier to explore and analyse over traditional non-immersive environment such as a desktop environment (Laha et al., 2014). Researchers investigating the effects of VR systems have run empirical studies that demonstrate significant benefits of an immersive VR environment for visualisation and exploration of 3D spatial datasets (Forsberg et al., 2008); (Zhang et al., 2003); (Zhang et al., 2001). VR as a visualisation platform can be used to visualise a very large number of data points (point cloud) in various shapes, sizes, and colours, enabling users to do real time exploration inside VR environment (Donalek et al., 2014). Additionally, VR technology integrated with a 3D input device can provide natural interaction with point cloud data using selection and navigation techniques (Section 2.4). 3D interaction can improve exploration around large point cloud data through its interface.

Integrating point cloud data into an immersive VR environment could potentially support structural estimation of a point cloud. VR's point cloud visualisation issues might be mitigated with human efforts, such as when observing the point cloud data from different views to estimate the structure of the point cloud (Prouzeau et al., 2019). However, structural estimation in VR-point cloud remains challenging.

There was an interest in developing domain-specific immersive analytics VR application due to the presence and engagement in VR as well as natural interaction from the input device (Batch et al., 2019). However, task performance in VR should be compared first with the domain's current practice, e.g. whether the task performance in VR was significantly different compare with the current practice.

VR could potentially be helpful in providing an environment for data collection in specific domains, especially domains which had challenging tasks due to the remote areas. An example is the forestry domain, when forest practitioners currently assess individual trees in the forest environment. Individual tree assessment in a forest can be difficult and risky. Challenges that exist when assessing trees in the field include weather, terrain condition, and vegetation complexity.

Incorporating VR-point clouds into individual tree assessment could potentially support forest practitioners by providing a safe environment, without having to perform the assessment in the challenging forest environment, and may also provide for more accurate assessments, particularly when complex and difficult field conditions are replaced by a virtual environment.

Forest inventory for radiata pine tree assessment requires measurement or estimation of various tree structures (Section 2.6) that may be suitable for estimation in VR-point cloud. It is interesting to explore whether these structures can be seen in VR-point cloud. If they can, then which structures could be revealed inside VR-point cloud and what is a practitioner's experience of assessing the radiata pine tree in VR-point cloud. *Forest practitioners can contribute by providing feedback about their experience and their impression of assessing radiata pine trees in a VR-point cloud*. Additionally, their *task performance can be compared with field assessment to learn the strengths and weaknesses of VR-point cloud and VR methods for radiata pine tree inventory assessment*.

Chapter 3 Research Questions, Goals, Contributions, and Methodology

3.1 Research Questions, Goals, and Contributions

As described in the previous chapter (Section 2.7), forests present a challenging environment because of weather, terrain condition, and vegetation complexity. This can make accurate forest inventory assessment difficult, time consuming, and risky in terms of workers' health and safety. Incorporating VR-point cloud methods into individual tree assessment could potentially support forest practitioners, allowing them to perform their assessments within an office rather than a challenging forest environment.

However, not every aspect of forest assessment is likely to be possible in VR. Task performance in VR needs to be compared first with a field assessment, allowing forest practitioners to provide contextual feedback on assessment in VR for the forest inventory.

Research question #1 focused on a task performance comparison between VR-point cloud assessment and field assessment to assess individual radiata pine trees. Research question #2 focused on the practitioners' contextual feedback about individual radiata pine tree assessment in a VR-point cloud environment. Below are the research questions for this research:

1. How does the task performance of individual radiata pine tree assessment in a VR-point cloud environment differ from the field assessment, measured in terms of accuracy?

2. From practitioners' contextual feedback, what is their experience and impressions of assessing individual radiata pine trees in a VR-point cloud environment?

This research focused on the following goals:

1. To compare the task performance of individual radiata pine tree assessment in a VR-point cloud environment with performance in a traditional field assessment.
2. To examine data that describes the experience and impressions of practitioners' attempting to assess inventory data in a VR-point cloud environment.

This research makes the following contributions:

1. It compares the performance of individual radiata pine tree assessment in a VR-point cloud environment with assessment in the field.
   Field assessment was used as ground truth for accuracy comparisons with VR task performance. The tasks comprised of inventory assessment of individual radiata pine trees. From the task performance, this research revealed the strengths and weaknesses of the VR-point cloud assessment compared to field assessments.

2. It analyses practitioners' contextual feedback about their experience of using a VR-point cloud environment for individual radiata pine tree assessment.
   The practitioners' contextual feedback helps to project how VR-point cloud visualisation methods might contribute to individual radiata pine tree assessment, and so to avoid the current field assessment difficulties when collecting inventory data in the field.

3.2 Research Methodology

Radiata pine tree assessment in a forest is challenging due to some difficulties in the forest such as weather, terrain condition, and vegetation complexity. Integrating radiata pine tree assessment into a VR-point cloud environment could provide a safe environment for forest practitioners, as well as could reveal the strengths and weaknesses of VR-point clouds for radiata pine tree assessment. The strengths and weaknesses of a VR-point cloud lead to research question #1 on the comparison of task performance between the VR-point cloud assessment and the field assessment. The performance in a VR-point cloud might be worse than in the field assessment because it can be shown that it is inherently more difficult for practitioners to visualise trees and tree structures in the VR-point cloud. The capacity of forest practitioners to provide contextual feedback about their experience of assessing trees in a VR-point cloud leads to research question #2.

Forest inventory for radiata pine tree assessment requires information on a variety of the structural elements of individual trees. The data collected for forest inventory includes tree diameter (in mm unit), tree height (in m unit), and tree quality assessment. Tree quality assessment is a stem structural estimation, assessed using different codes representing the structure size/condition (Section 2.6). According to the data type for forest inventory, quantitative methods are suitable to analyse the task performance, such as diameter assessment, height assessment, and tree quality assessment. Quantitative methods emphasise the objective measurements and numerical/categorical analysis from the data (Babbie, 2016).

Practitioners' contextual feedback about their experience of tree assessment in VR depends on how they used VR for inventory operation. Depending on the type of feedback, some feedback is measurable and some other feedback is not measurable. Measurable feedback is objective, such as a Likert scale in a questionnaire, where there are different categories representing each scale/score. In this case, measurable feedback can be analysed using quantitative methods. However, if the feedback is not measurable (e.g. comprised meanings and qualities of certain assessment) then quantitative methods are not suitable to analyse the feedback. Qualitative methods are suitable to analyse non-measurable feedback because they allow a robust understanding of a certain topic and can reveal the meaning of certain assessment or condition (Leavy, 2017).

This research was one component of a larger project supported by FWPA (Forest and Wood Products Australia Limited, with project number PNC464-1718). This research was undertaken by a collaboration of university researchers and industry partners. The radiata pine tree data for the VR-point cloud were provided by Interpine Innovation, Rotorua, New Zealand (Interpine Group Ltd, 2020). Interpine is a commercial provider of forest inventory services, with a strong commitment to research, development, and technology transfer. Interpine staff participated in the experimental components of the project (Chinthammit, 2019). The experiment comprised structural estimation assessments (height assessment, diameter assessment, branch assessment, sweep assessment, and feature assessment) with post-experiment feedback. The details about the experiment can be found in Section 4.2. Some of the data from the experiment are suitable for this research, such as task performance data and feedback data. Therefore, this research collected those data from the experiment as core data for analysis.

The overall research design is illustrated in Table 3. Data collection comprised the experiment undertaken with Interpine staff. The experiment aimed to collect structural estimation assessments data in VR as performed by the Interpine staff, as well as post-experiment feedback data provided by the Interpine staff. The data required for this research (task performance data and feedback data) were selected from the data from the experiment. The data were analysed according to the data type as explained in the previous paragraphs.

Table 3: Research Design.

Research Goals	Data Collection	Selection of key components of data	Analysis	Findings
Task performance comparison with field assessment	Experiment	Task performance data	Quantitative	List of all the findings from the analyses to answer research questions
Possibility of tree assessment in VR based on practitioners' feedback		Feedback data	Qualitative, Quantitative	

Chapter 4 Data Collection

This chapter describes inventory task procedure in the field assessment in Section 4.1, data collection in Section 4.2, selection of key components of data in Section 4.3, and data analysis methods from the research design outlined in Chapter 3 (Section 3.2, Table 3) in Section 4.4. Results are separately presented and discussed in Chapter 5.

4.1 Inventory Task Procedure in the Field Assessment

This section describes the inventory task procedure in field assessment, based on the collected data for forest inventory outlined in Section 2.6: tree diameter, tree height, and tree quality assessment (branch, sweep, and features). During field assessment, forest practitioners would bring forest inventory gears, such as a measurement tape and a reference card, as shown in Figure 11 [Left]. Each inventory task procedure in the field assessment is outlined as follows:

- Tree diameter: the tree diameter was measured with a measurement tape at the outer bark of the tree at 1.3 m height.
- Tree height: the tree height was measured with a laser rangefinder, by capturing the estimated peak of the tree.
- Branch assessment: the branch was measured by approximation based on the visual reference card shown as Figure 11 [Right].
- Sweep assessment: the sweep was measured by approximation from the longest to the shortest lengths of sweep (e.g. from 6 code, L code, then S code).
- Features assessment: some features were measured by a measurement tape, e.g. to measure the size of the nodal swelling. Other features were noticeable with naked eye in the field assessment.

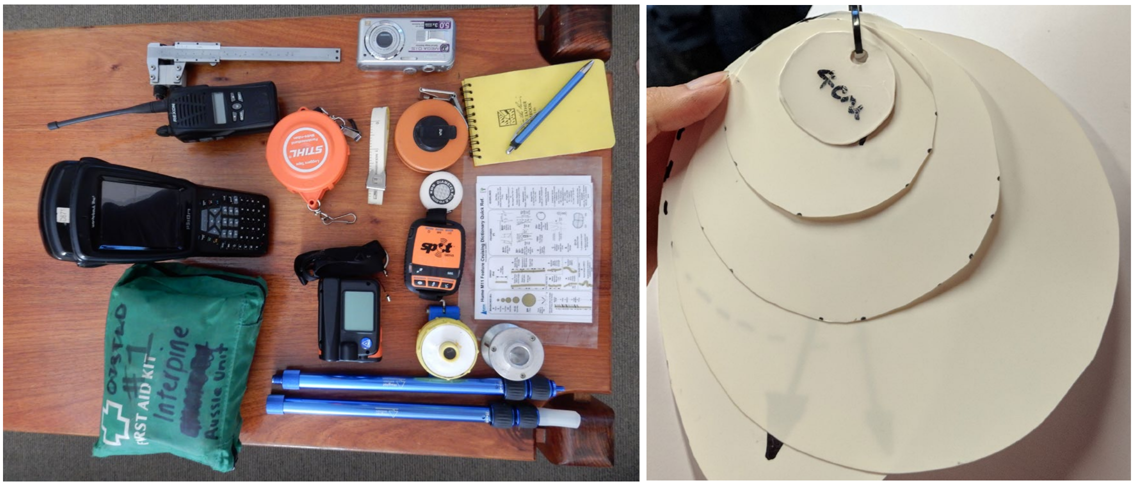


Figure 11: Copyright 2020 by Interpine Group Ltd. [Left] Forest inventory gears. [Right] Visual reference card for branch assessment.

4.2 Experiment

This section describes the data collection, based on the research design illustrated in Table 3 (Chapter 3, Section 3.2). The data source was an experiment undertaken for the FWPA project. The experiment was participated by Interpine staff and was conducted from 27th – 31st August 2018 at Interpine headquarter in Rotorua, New Zealand (Chinthammit, 2019). I was the researcher who conducted the experiment. The hardware used for the experiment was an Alienware 17 R4, with processor Intel® Core™ i7-7820HK 32GB, CPU @ 2.90GHz, 2901 Mhz, 4 Core(s), and 8 Logical Processor(s). The VR devices used for the experiment were an Oculus Rift and Touch controllers (right-hand and left-hand controllers) from Facebook (Facebook Technologies, 2020). During the experiment, participants wore a VR headset and held two hand controllers.

The VR application used in the experiment was developed with Unity3D from (Unity Technologies, 2020). The VR tools used in the experiment was developed as part of the FWPA project (Chinthammit, 2019). The VR tools comprised navigation tools and measurement tools. Figure 12 illustrates the VR tools. Navigation tools included hand controllers' joystick navigation and teleport function. Joystick navigation was used to navigate horizontally or vertically in VR-point cloud environment. Teleport function was used to teleport to a specific location. Measurement tools included a height tool (for tree height assessment), a circle tool (for diameter assessment), and a branch tool (for branch assessment). Table 4 describes the mechanism for each of the VR tools.

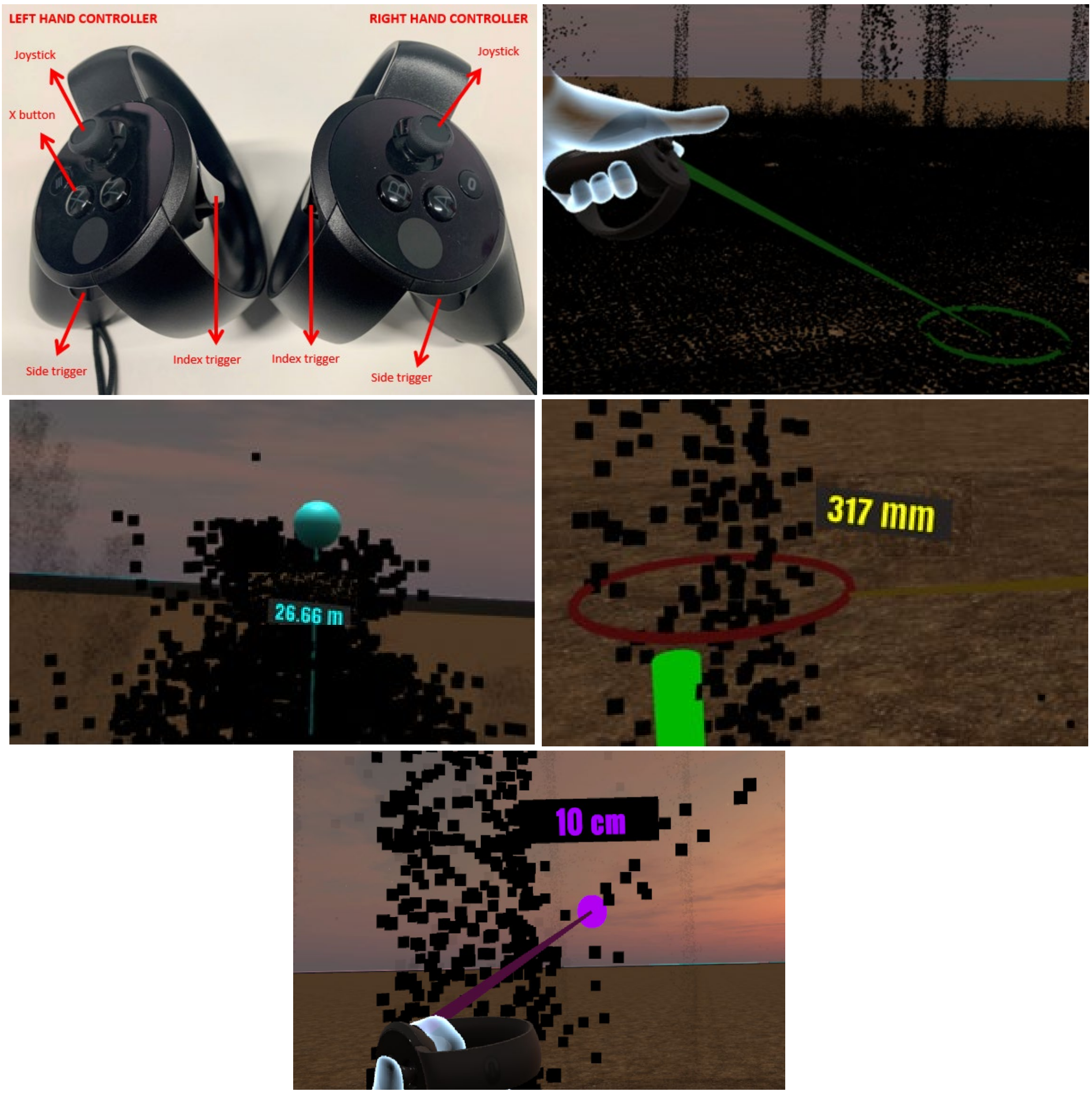


Figure 12: [Top left] Hand controllers of Oculus Rift. [Top right] Green circle on the ground showed a targeted position in teleport function. [Middle left] Height tool. The blue ball located the tree height (26.66 m). [Middle right] Circle tool. The red circle showed tree diameter (317 mm). [Bottom] Branch tool. The purple circle showed a branch node, with 10 cm diameter size.

Table 4: Mechanisms for VR tools.

VR Tools	Mechanism
Joystick navigation	- *Left-hand controllers (illustrated in Figure 12)* Push the joystick to navigate to horizontal axis direction (left, right, forward, backward). - *Right-hand controllers (illustrated in Figure 12)* Push the joystick forward/backward to navigate to vertical axis direction (up and down).
Teleport function	1. Hold down the side trigger on the left-hand controller to bring up the targeted position intersecting with the floor plane. 2. Press the index trigger on the left-hand controller to instantly teleport to the targeted position.
Height tool	1. Hold down the side trigger on the right-hand controller to bring up the point laser selection. 2. Point the laser at a point on the VR ground plane. Aim at the bottom of the measured tree. Press the index trigger on the right-hand controller to create the first ball (one end of the line). 3. Elevate to the top using joystick on the right-hand controller. 4. Aim at a point at the top of the measured tree. Hold down the X button (left hand controller) and side trigger (right hand controller) to create the second ball (another end of the line). 5. The line node and tree height are automatically calculated and displayed after creating the second ball, as shown in Figure 12.
Circle tool	1. Hold down the side trigger on the right-hand controller to bring up the point laser selection. 2. Point the laser at 1.3 m height above the VR ground. 3. Press the index trigger on the right-hand controller to create a lasso. 4. The diameter size is automatically calculated after the lasso created, as shown in Figure 12.
Branch tool	1. Hold down the side trigger on the right-hand controller to bring up the pointer laser selection. 2. Point the laser at a point of a tree branch that you want to place the branch node on. 3. Press the index trigger on the right-hand controller to create a branch node. 4. The size of the branch node that will be created can be changed by pressing the X button on the left-hand controller. The size of the branch node is only to help branch size estimation, therefore the branch size's decision is from the participant.

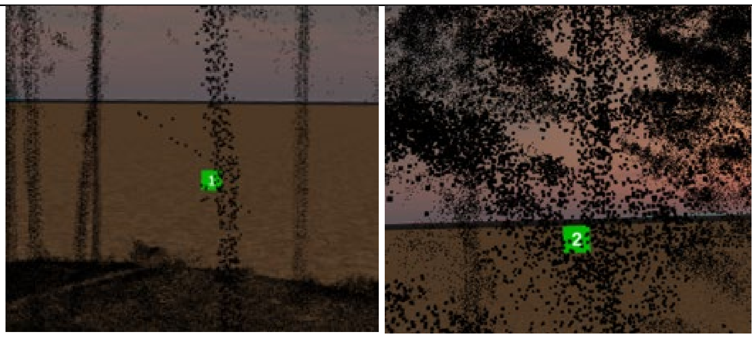
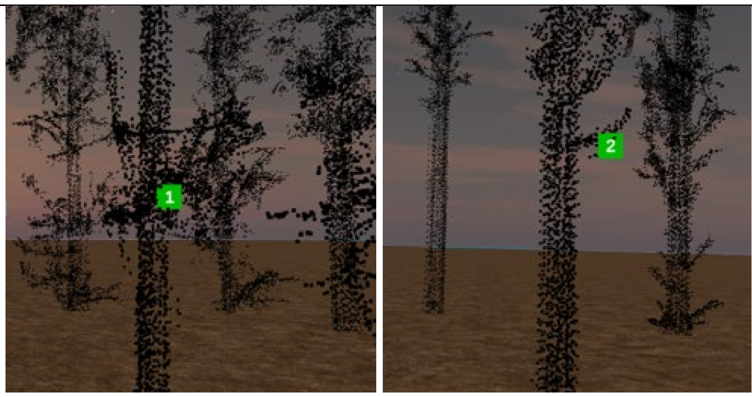
The experiment comprised of five different tasks, as shown in Table 5. The tasks sequence was as follows: feature assessment, height assessment, sweep assessment, diameter assessment, and branch assessment. The sequence was decided based on alternate usage of the measurement tools. For example, height and diameter assessments were in between other assessments because the assessments used height tool and circle tool respectively. Branch tool was optional for participants. In other assessments (sweep and feature), participants roughly estimated the structure type and structure size. There were 5 different forest plots used for the experiment with an average of 20 trees for each plot (minimum 10 trees; maximum 25 trees). Each forest plot was obtained from a 60-meter height of a flying drone. The spatial density range for the height was 8000-12000 points/m^2.

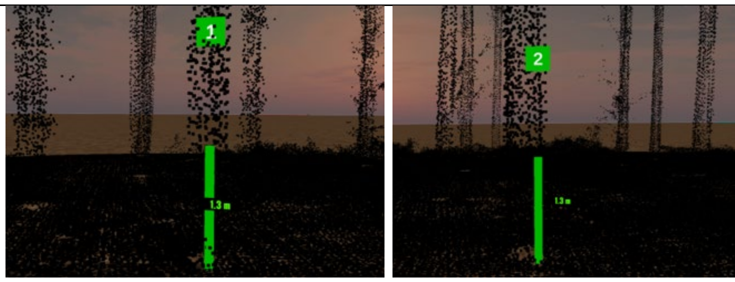
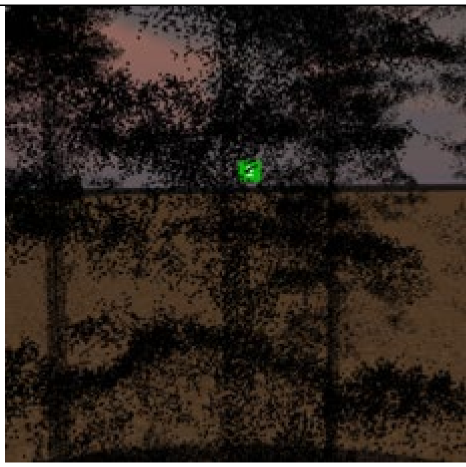
Each forest plot was assigned to an assessment based on the following assessment criteria:

- Forest plot #1: the trees on this forest plot are straight (less stem curvature) with no broken tree-top which are appropriate for height assessment.
- Forest plot #2: the trees on this forest plot mostly have dense points at 1.3 m, which is the required height for diameter assessment.
- Forest plot #3: this forest plot has variations of branch sizes, including the biggest (10 cm) one, therefore suitable for branch assessment.
- Forest plot #4: this forest plot has variations of sweep structures such as kink (K) and gentle sweeps (L and S), therefore suitable for sweep assessment.
- Forest plot #5: this forest plot has variations of features such as spike knot and damage, therefore suitable for feature assessment.

Table 5 shows the number of items required for each assessment. Not only trees for assessments, but also some surrounding trees are displayed in Table 5 to show VR-point cloud environment conditions for each task. In the experiment, trees for each assessment were marked in green tags so that participants could find out easily which tree(s) should be assessed in each task. Some green tags were located at the canopy, such as in feature assessment, sweep assessment, and branch assessment.

Table 5: Tasks sequence in the experiment, along with corresponding forest plots, number of items for each task, and trees used for the experiment.

Tasks Sequence	**Forest Plots**	**No. of items**	**Trees used for assessment (marked in green tag)**
Feature assessment	#5	2 features	 Green tags showed the locations of the features. The right one was located at the canopy.
Height assessment	#1	2 heights	 Green tags showed the trees for height assessment.

Sweep assessment	#4	2 sweeps	 Green tags showed the locations of the sweeps, which were at the canopy.
Diameter assessment	#2	2 diameters	 Green tags showed the trees for diameter assessment. The green 1.3 m bars (from the VR ground plane) were the required height for tree diameter.
Branch assessment	#3	1 branch	 Green tag showed the branch location, which was at the canopy.

The experiment was conducted one participant at a time using the following procedures:

1. *Introduction (estimated time spent: 5 minutes):*
   The participant was provided with an information sheet detailing the purposes of the experiment and was required to sign a consent form before taking part in the experiment. The consent form and the information sheet are attached to this thesis as Appendix A and B respectively.
2. *Familiarisation with VR application (estimated time spent: 2 minutes):*
   The participant was provided with an overview of the VR application. This included an introduction to the VR application, the VR headset, the Touch controllers, and the point cloud dataset.
3. *Training and testing of the tasks with VR tools (time limit: 1 hour per participant):*

The process of training and testing was within each task, based on the task sequence defined in Table 5. The following steps are the process of training and testing of the tasks:

a. The participant was demonstrated on how to use a relevant VR tool required to perform each task.
b. The participant practised using the VR tool.
c. The participant was then asked to perform the task on the pre-selected trees that were different from the practice samples.

4. *Post-experiment feedback (estimated time spent: 10-15 minutes):*
Each participant was asked to fill out a questionnaire to provide feedback about the experiment. The questionnaire is attached to this thesis as Appendix C. The questionnaire collected the feedback from the participants that described their experience of using the VR-point cloud application to undertake tree assessments. There are four sections in the questionnaire:
    a. *Section 1: pre-experiment data collection*
    This section collects each participant's demographic data (age and gender), prior experience with VR, and expertise in forest inventory.
    b. *Section 2: subjective feedback on the use of the VR tools*
    This section collects each participant's subjective ratings on the use of the navigation tools. There are two types of feedback: Likert scale and open-ended written feedback.
    c. *Section 3: subjective feedback on the VR inventory tasks*
    This section collects each participant's subjective ratings about the five tasks. There are two types of feedback: Likert scale and open-ended written feedback.
    d. *Section 4: other feedback*
    This section collects each participant's impression about the consistency of the VR with their real-world experiences and their confidence in the adoption of the VR technology. There are two types of feedback: Likert scale and open-ended written feedback.

4.3 Data Selection

This section describes the selection of key components of the data, as illustrated in Table 3 research design (Chapter 3, Section 3.2). The selected key components of data were obtained from the Interpine experiment (Section 4.2). Given the research goals, specific data from the experiment were selected for this research.

The first research goal was related to task performance in the VR environment compared with field assessment. As noted in the literature review, there are five tree assessments: diameter assessment, height assessment, branch assessment, sweep assessment, and feature assessment. Table 6 shows the selected key components of data for the first research goal.

Table 6: Task performance data: selected data from Experiment (Section 4.2) for task performance comparison with the field assessment.

Tasks	No of item(s)	Forest Plot
Height assessment	2 heights (*Height1* and *Height2*)	1
Diameter assessment	2 diameters (*Diameter1* and *Diameter2*)	2
Branch assessment	1 branch	3
Sweep assessment	2 sweeps (*Sweep1* and *Sweep2*)	4
Feature assessment	2 features (*Feature1* and *Feature2*)	5

The second research goal was related to practitioners' feedback about their experience of tree assessments in the VR-point cloud environment. To address this goal, this research explored the questionnaires completed in the post-experiment. Only feedback about VR cruising tasks (tree assessments in VR), VR consistency with real world assessment, and adoption of the VR technology to replace field-based data collection were required for the second research goal. The selected key components suitable for the second research goal were feedback about: tree assessments in VR, VR consistency with real world assessment, and participants' confidence in the adoption of the VR technology to replace field-based data collection. Table 7 shows different components or topics from the collected feedback. Each topic comprised both quantitative (5-point Likert scale questionnaire) and a qualitative (open-ended written feedback) subjective feedback.

Table 7: Feedback data: practitioners' feedback from the questionnaire.

Topics (from Questionnaire)	Feedback Type
Tree assessments in VR	Likert scale and open-ended written feedback
Consistency with real world assessment	
Adoption of the VR technology to replace field-based data collection	

4.4 Data Analysis Methods

This section describes the methods used to analyse the data. There were two analyses applied in this research: (1) analysis of task performance and (2) analysis of practitioners' feedback.

Task performance analysis focused on comparing the accuracy of the VR assessment tasks with the field assessment data. The field assessment data for each task were provided by Interpine. The height and diameter assessment data were analysed quantitatively using descriptive statistics: a measure of central tendency (mean) and measure of spread (standard deviation). The branch, sweep, and feature assessment data were non-numerical (categorical), therefore, the analyses were based on the participants' responses/answers (Bairagi and Munot, 2019).

As already described, there were two types of practitioners' feedback: Likert scale responses and open-ended written feedback, with all feedback divided into several topics, as shown on Table 7. Likert scale responses were analysed quantitatively for each task based on the frequency/percentage of each scale. Written feedback was analysed qualitatively using coding (Burnard et al., 2008). Each topic represented each category for coding. First, initial coding was created from the written feedback containing several words or phrases. Then, there was a removal of duplicated words or phrases from initial coding. After that, these phrases were grouped into designated categories as final coding. Finally, a report was prepared based on the final coding.

Chapter 5 Results and Data Analyses

5.1 Participants

The total number of participants for the experiment was 31 people of age between 18-62 years and length of forest expertise between 6 months to 38 years. However, each assessment had a different number of participants due to time constraints. The experimental session was limited to one hour per participant. Due to the time constraint, some participants could not complete the assessment: 17 participants from branch assessment, 7 participants from diameter assessment, and 5 participants from height assessment, sweep assessment, and feature assessment. The participants details are shown as Table 8. There were 4 participants who had no experience in forest inventory. Their occupations were IT manager, forest scientist, planner, or analyst.

Table 8: Participants details.

Forest Expertise	Number of Participants				
	Height Assessment	Diameter Assessment	Sweep Assessment	Branch Assessment	Feature Assessment
Crew Leader	8	7	8	5	10
Second-in-Charge	6	6	7	4	6
Auditor	3	3	3	2	3
Forest Inventory	2	2	2	1	2
Consulting	3	3	3	1	3
IT Manager	1	1	0	0	0
Forest Scientist	1	1	1	1	1
Planner	1	0	1	0	1
Analyst	1	1	1	0	0
Total participants who completed the assessment	26	24	26	14	26

5.2 Results and Analyses of Task Performance

This section presents the results and analyses of task/assessment performance, compared to field assessment. There were five assessments that focused on different structure estimation tasks: height assessment, diameter assessment, branch assessment, sweep assessment, and feature assessment. The assessments are discussed separately under each sub-section so that the analyses of task performance can be discussed according to each structure.

5.2.1 Height Assessment

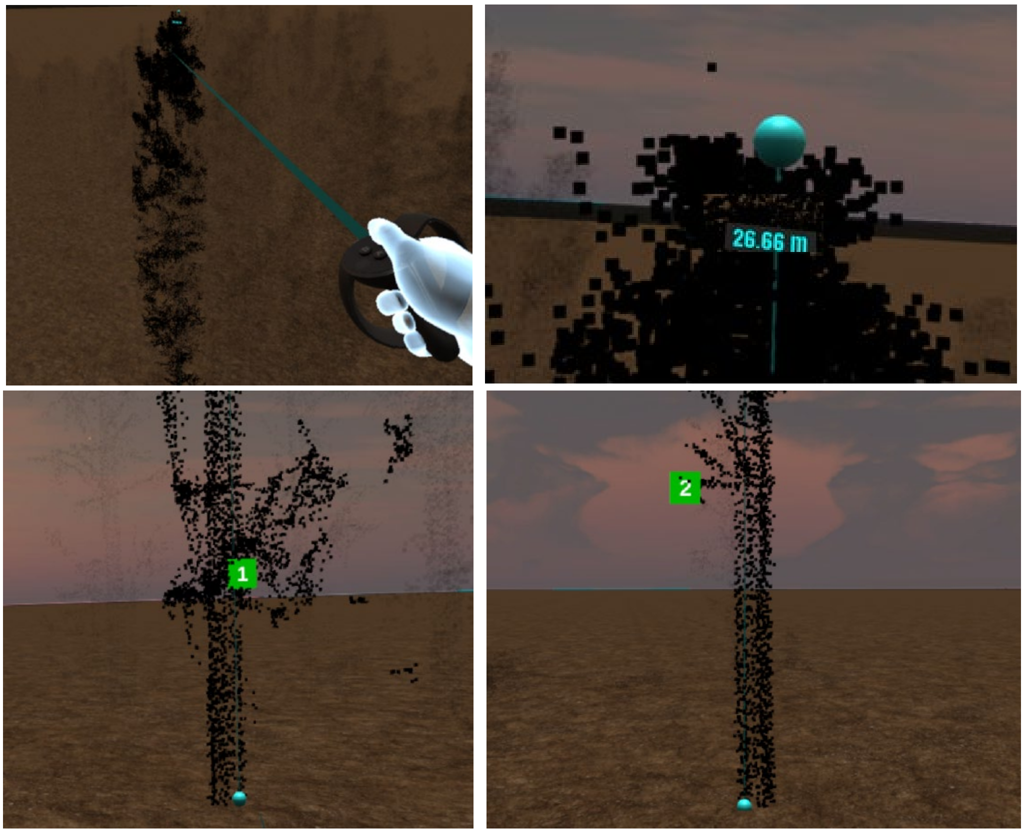


Figure 13: [Top Left] Zoomed-out image of the tree - showing a blue laser pointer from hand controller. [Top Right] Zoomed-in image of the tree - showing a height tool (blue line with blue ball at the end of the line) at one end point on the peak of the tree. The number next to the peak of the tree showed a height measurement which was automatically calculated by the height tool. [Bottom Left and Right] Two tagged trees (green square attached on the tree) used in height assessment. The blue ball at the end of the blue line on each tree showed a measurement end point on the VR ground plane.

Tree height was assessed using height tool. The mechanism of the height tool has been explained in Table 4 of Section 4.2. Figure 13 [Top Right] shows the height tool used for assessing tree height. The field data for height assessment were acquired from a forest plot (Section 4.2, Table 5). There were two heights assessed in the forest plot, as shown in Figure 13 [Bottom Left and Right]: *Height1* and *Height2*.

Unfortunately, the experiment incorrectly used a non-normalised forest plot for height assessment. As shown in Figure 14 [Top Right, Bottom Right], in the non-normalised forest plot some parts of the lower stem and the forest plot ground were not visible as they were covered by the VR ground plane. VR ground plane was used to define a ground height (0.0 m), where anything below will not be visible to the user.in As a result, there was a missing height in the non-normalised forest plot. An attempt was made to explain the experiment data in height assessment by compensating for a missing height to avoid misinterpretation of having large errors. The missing height was calculated using the height tool by manually measuring the distance from the offset point to forest plot ground. For *Height1*, the missing height was approximately 1.11 m. For *Height2*, the missing height was approximately 2.73 m. These missing heights were automatically calculated by the height tool.

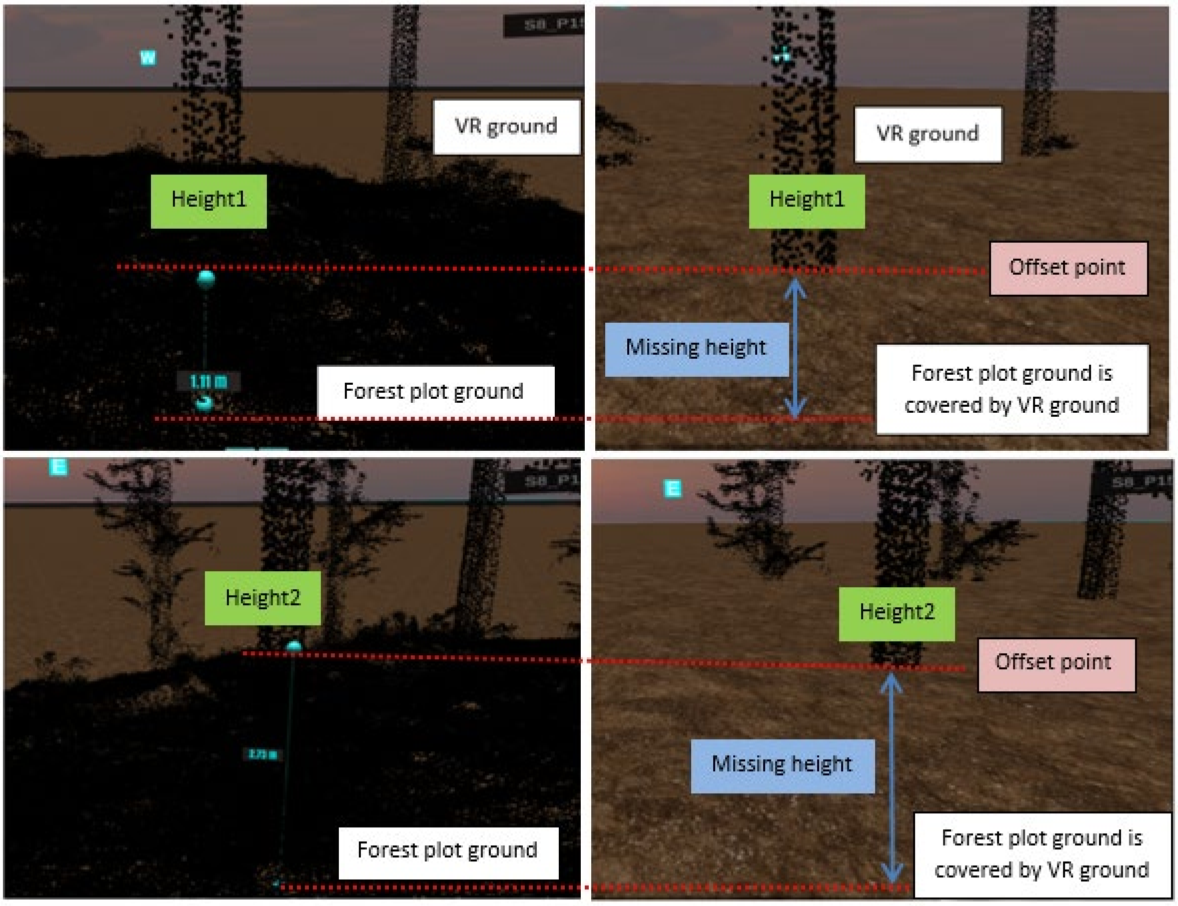


Figure 14: [Top Left, Bottom Left] Normalised forest plot. The height tool calculated the missing height from the offset point to the forest plot ground: 1.11 m for *Height1* and 2.73 m for *Height2*. [Top Right, Bottom Right] Non-normalised forest plot used for height assessment in the experiment. In the non-normalised forest plot, some parts of the lower stems and the forest plot ground were covered by the VR ground, resulting in missing height.

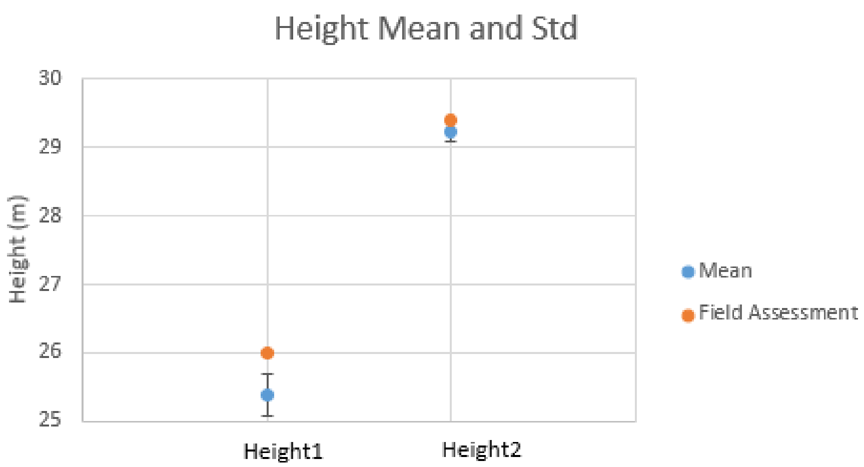
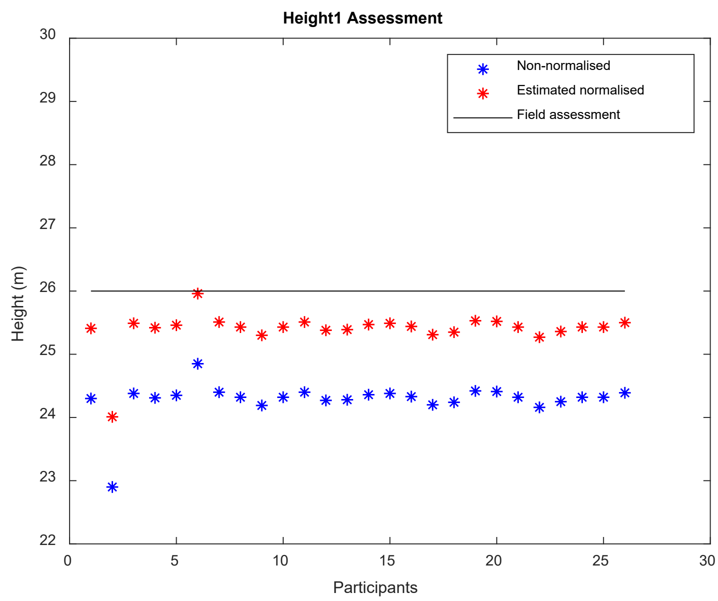


Figure 15: Means and standard deviations (std) for *Height1* and *Height2* based on the estimated normalised assessment.

Figure 15 illustrates the mean and standard deviation (std) value for *Height1* and *Height2*. *Height1* mean (25.4 m) and *Height2* mean (29.2 m) were assessed based on the estimated normalised assessment. The means for *Height1* and *Height2* were relatively closed with the field assessment (*Height1* field assessment = 26 m, *Height2* field assessment = 29.4 m). The consistencies of the height assessments in the VR environment expressed in terms of the standard deviation were std 0.3 m for *Height1* and std 0.2 m for *Height2*.

Figure 16 shows *Height1* [Top] and *Height2* [Bottom] assessments in the non-normalised forest plot (used in the experiment), the estimated normalised forest plot, and the field assessment. The accuracy was assessed based on the estimated normalised forest plot by using a demerit calculation (Section 2.6). Height assessment has a tolerance of ± 1.0 m from the field assessment, then incurs 2 demerits per 0.5 m difference. There was only one participant in the *Height1* assessments that incurred demerits (exceeded the tolerance allowance), attracting 4 demerits. Therefore, there were 4 demerits for *Height1* from this participant. None of the estimates in the *Height2* assessment incurred demerits. Therefore, *Height2* had 0 demerit, which means the difference between VR assessment and field assessment was within the tolerance allowance (± 1.0 m from field assessment). According to Interpine Group Ltd, the demerits for height assessment in the field can vary from 1-5 demerits (sometimes more, maybe 15 demerits) on average per tree. There could be one out of eight trees may incur demerit, generally because the forest practitioner did not reach the top of the tree (incorrectly collected tree height) or the tree was leaning.



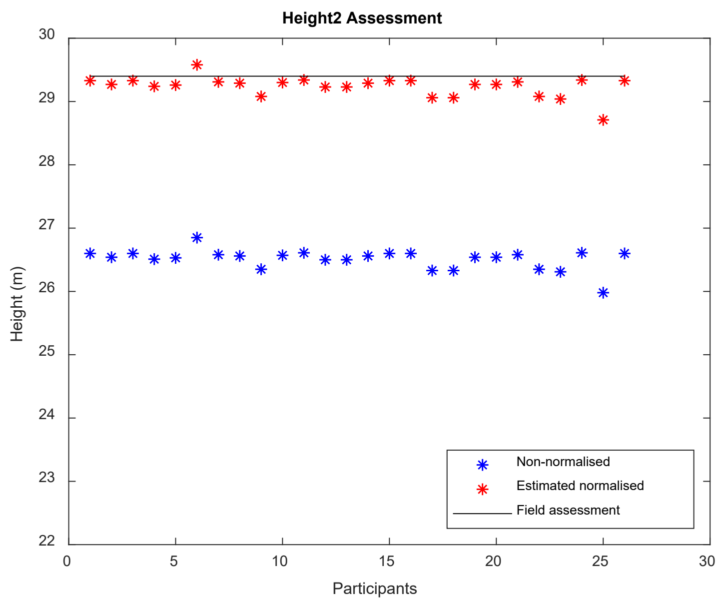


Figure 16: [Top] Participants' *Height1* assessment from non-normalised, estimated normalised, and field assessment. *Height1* demerit (4) was calculated based on the estimated normalised forest plot. [Bottom] Participants' *Height2* assessment from non-normalised, estimated normalised, and field assessment. *Height2* demerit (0) was calculated based on the estimated normalised forest plot.

There were differences with the field assessment after factoring in the estimated missing height from the non-normalised forest plot. The reason behind the difference would seem to stem from individual participant's decision in choosing the point cloud data using the height tool, which were points chosen from the VR ground plane or from the peak of the tree. Figure 17 illustrates this condition: the blue dots represented the point cloud data at the peak of the tree and the orange dots represented participants' point selection. As seen from Figure 17, there were several different locations of orange dots, which represented the participants' subjective decision in choosing the highest point in height assessment.

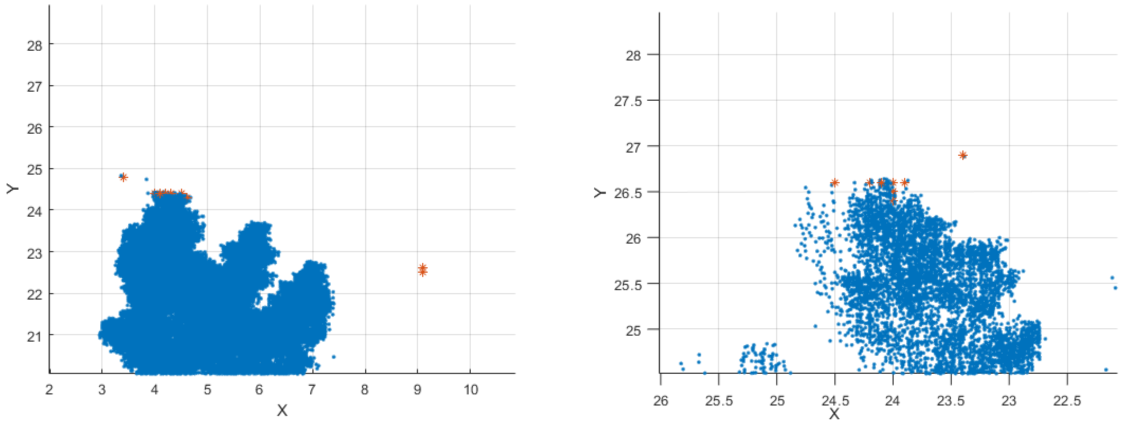


Figure 17: Participants' point selection (orange dots) at the peak of the tree in *Height1* [Left] and *Height2* [Right]. X-axes represented the horizontal VR-point cloud area in meter unit, while Y-axes represented the vertical VR-point cloud area in meter unit.

5.2.2 Diameter Assessment

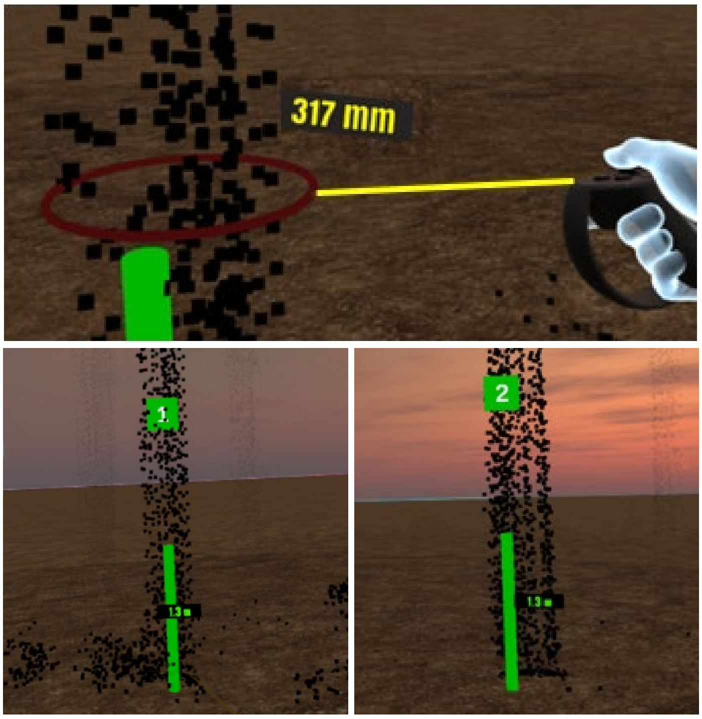


Figure 18: [Top] Circle tool (red circle with yellow line/lasso) used for assessing tree diameter. The number next to the red circle showed a diameter measurement which was automatically calculated by the circle tool. [Bottom Left and Right] Two tagged trees (the green squares are the tags) used in diameter assessment. The green 1.3 m bar was the required stem height for tree diameter assessment.

As noted in Section 2.6, tree diameter in the field assessment was measured 1.3 m above the ground (also refer to Figure 18 [Bottom Left and Right] for the 1.3 m green bars). The same diameter assessment was used in the VR-point cloud at 1.3 m above the ground. This was implemented in the VR application by creating a lasso using a circle tool covering the tree diameter. Figure 18 [Top] shows that areas around the tree diameter in the VR-point cloud consisted of points forming a tree stem-like structure. The field data for diameter assessment were acquired from a forest plot (Section 4.2, Table 5).

There were 24 participants in the diameter assessment experiment. There were 2 diameters assessed in the forest plot as shown as Figure 18 [Bottom Left and Right]: *Diameter1* and *Diameter2*. Figure 19 shows the means and standard deviations (std) for *Diameter1* and *Diameter2* assessments. The mean for *Diameter1* was 571 mm with the field assessment 461 mm, while the mean for *Diameter2* was 494 mm with the field assessment 345 mm. The consistencies of the diameter assessment made in the VR-point cloud environment expressed in terms of the standard deviation were std 53.7 mm for *Diameter1* and std 43.9 mm for *Diameter2*.

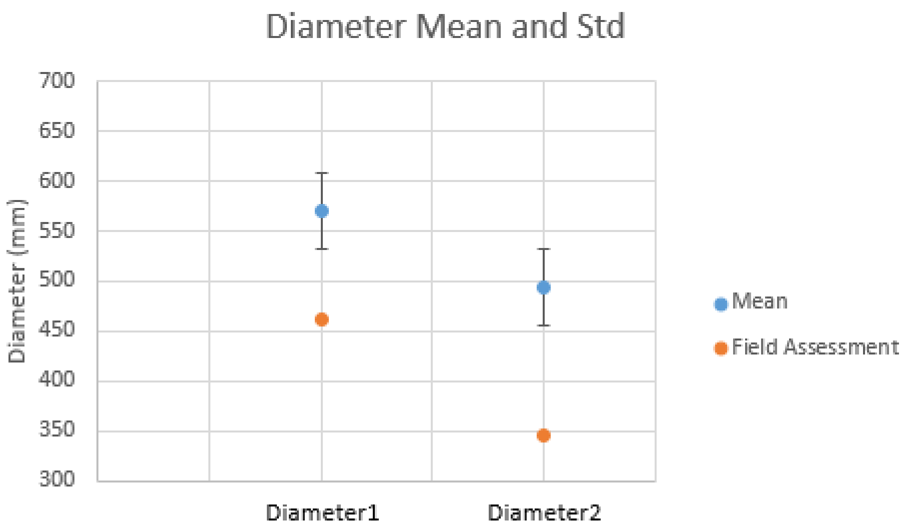


Figure 19: Diameter assessment mean and standard deviation (std).

The accuracy was measured from the demerit calculation (Section 2.6) of diameter assessment. Diameter assessment has a tolerance of ± 5 mm then incurs 1 demerit per 1 mm. Participants' demerit calculation for *Diameter1* and *Diameter2* is shown as Figure 20 [Top]. The maximum acceptable demerit for diameter assessment was set by inventory protocols to be 15 per tree. The demerits from diameter assessments (both *Diameter1* and *Diameter2*) were considerably large as they exceeded the maximum acceptable demerit. The averages of each participant's demerit were 104.5 for *Diameter1* and 144 for *Diameter2*. According to Interpine Group Ltd, the demerits for diameter assessment in the field can vary from 5-15 demerits per tree, depending on the forest practitioner's experience.

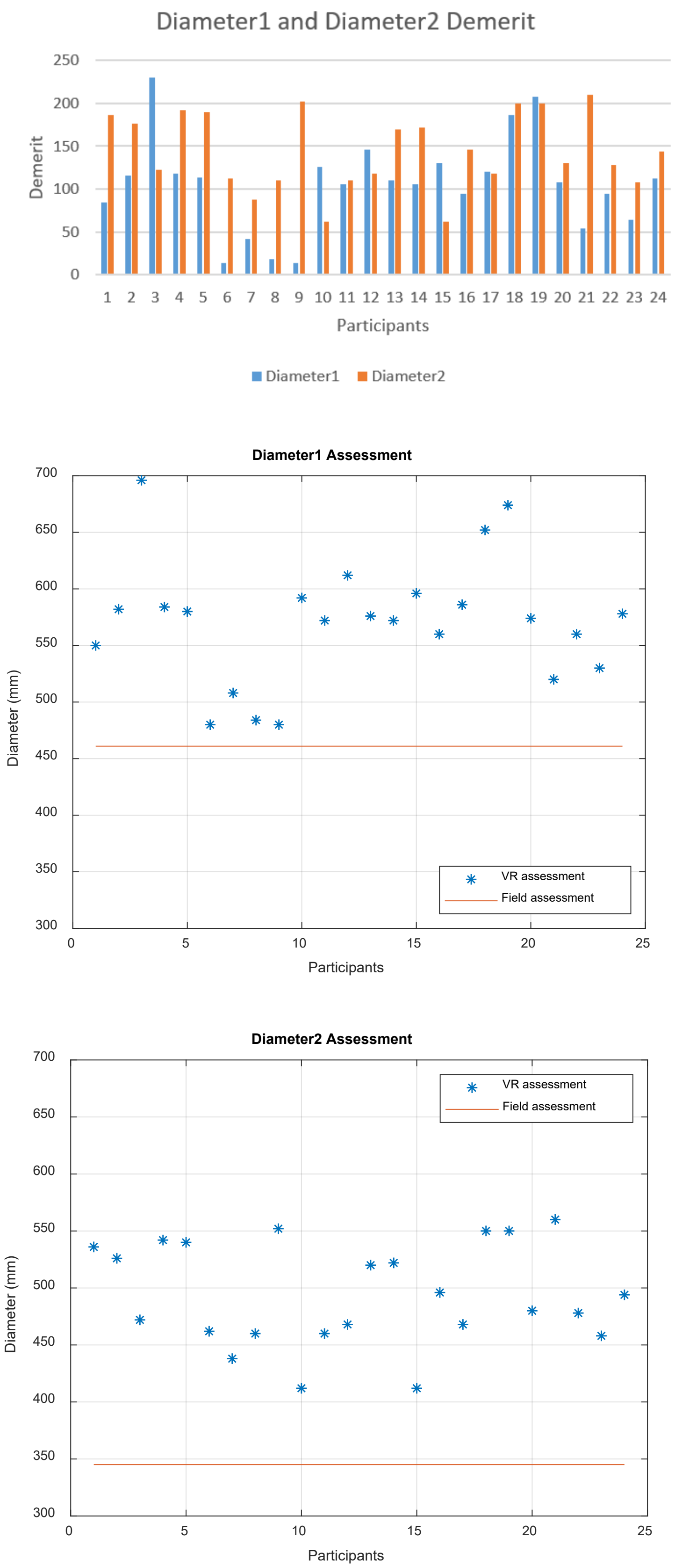


Figure 20: [Top] Participants' demerit in *Diameter1* and *Diameter2*. Diameter assessment has a tolerance of ± 5 mm then incurs 1 demerit per 1 mm. [Middle] *Diameter1* assessment in the VR-point cloud and in the field. The average of each participant's demerit for *Diameter1* was 104.7. [Bottom] *Diameter2* assessment in the VR-point cloud and in the field. The average of each participant's demerit for *Diameter2* was 144.

The accuracy from the demerit calculation was low because of what appears to be a consistent difference between VR-point cloud assessment and field assessment across all participants. The differences in diameter sizes and positions might be due to different participants' visual estimation when assessing structure around a tree diameter that consist of points. Participants would need to create a lasso using the circle tool when assessing the structure around the tree diameter at 1.3 m height. The lasso shape was fixed to circular-shaped lasso. The diameters of the lassos were automatically calculated. Each participant accommodated his/her own visual estimation when assessing the structure around the tree diameter and creating the lasso that caused the diameter size and position varied across participants. Some participants thought that the size was big enough as long as the lasso covered the outer points of the structure around tree diameter, and some of them might not double check whether their lasso properly covered the outer points of the structure. Figure 21 shows the evidence of different participants' estimation when assessing a tree diameter.

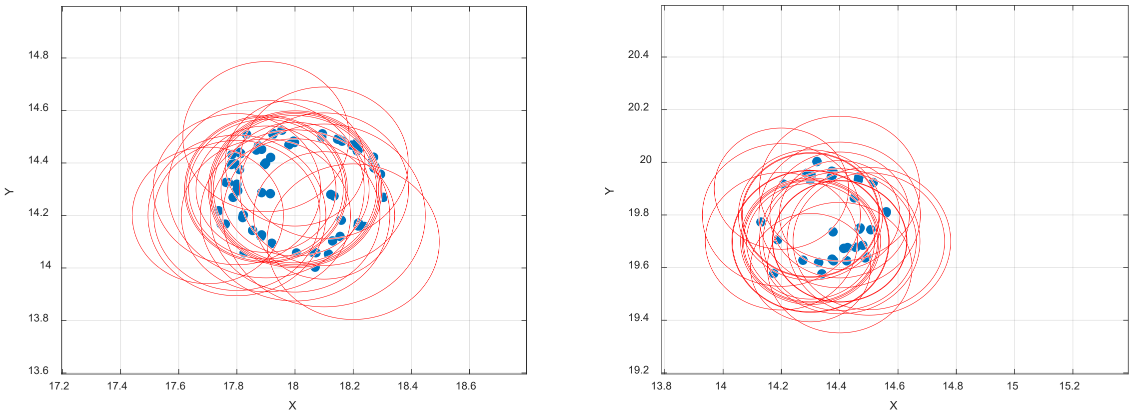


Figure 21: Cross section of lasso sizes and positions as results of participants' different visual estimation in assessing structure around a tree diameter for *Diameter1* [Left] and *Diameter2* [Right], with X and Y represented the VR-point cloud area in meter. Red circles were the lassos created by the participants, the blue dots represented the point cloud structure from 1.2 m to 1.4 m above the VR ground plane.

5.2.3 Branch Assessment

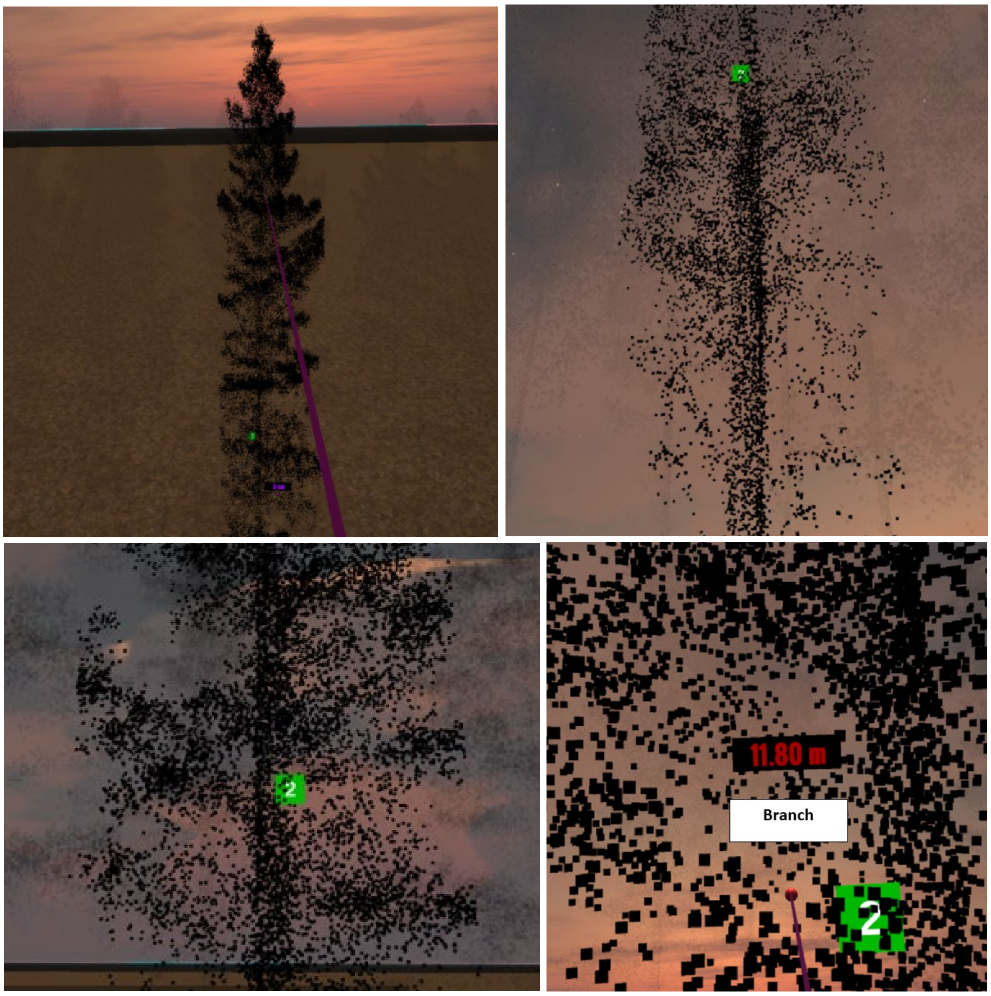


Figure 22: Tree used for branch assessment in the experiment. Green tag located the branch position that should be estimated by participants. [Top Left] Tree view from a distant. The purple line was from the participant's position. [Top Right] Tree view from the VR ground. [Bottom Left] Tree view from higher up the ground, in front of the branch. [Bottom Right] Zoomed-in view of the branch used for the experiment. The branch was located at 11.8 m height from the VR ground.

Branch assessment focused on assessing a branch diameter size. As illustrated in Figure 22 [Bottom Right], in the VR-point cloud the branch diameter comprised several points forming a branch-like structure on the stem of the tree. As noted in Section 2.6, there were several branch codes used in branch assessment in the field when determining the maximum branch diameter size in centimetres unit. There was one branch used in this experiment. The field assessment code for this branch was 10. Fourteen participants contributed to the branch assessment experiment. During the experiment, participants would call whatever branch code they noticed near the green tag and their answers were recorded manually by the researcher.

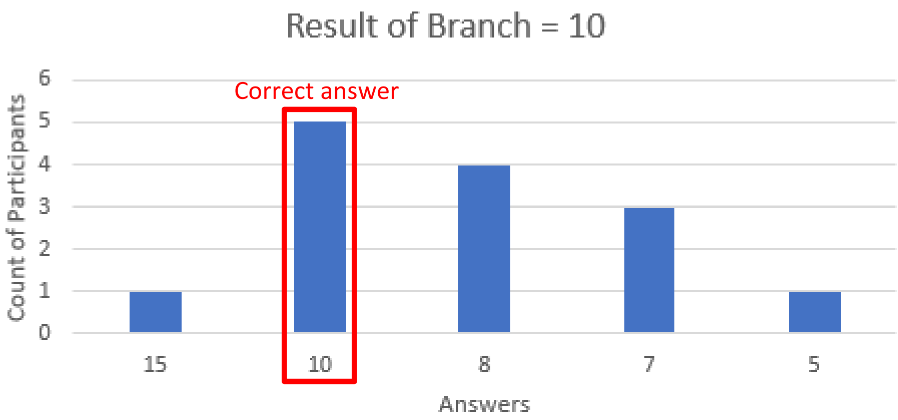


Figure 23: Participants' answers for branch assessment from the biggest to smallest branch size.

The order of the branch diameter size according to the branch code is 0, 5, 7, 10, 15, and 999 (> 15cm), from the smallest to biggest size in cm. As seen from Figure 23, there were 5 participants answered correctly (10 code), and that was the highest count of participants among other answers. Nine participants did not answer correctly.

There were four participants answered 8 code, which was not in the code list. It was possible that this happened due to any of the two factors. First, the participants might not have remembered exactly the order of the branch code. During the experiment, participants were asked to estimate the branch diameter size without a detail instruction of the code options. The available code options were only 0, 5, 7, 10, and 15. Participants had access to a reference card if only they requested. Therefore, participants might refer to the branch codes that they were most familiar with. Second, 8 code was likely accounted for 7 code or 10 code (the nearest size in cm) from participants' previous knowledge.

There was one participant answered 5 code, three participants answered 7 code, and one participant answered 15 code. According to the branch code category, the two codes (5 code and 7 code) are one category below and another code (15 code) is one category above the correct answer (10 code). The difference between these answer categories might be due to the different participants' visual estimation in estimating the branch size.

Estimating branch diameter size might be difficult in VR. As reflected in Figure 22, the branch could be inspected from several different positions during the assessment. The different positions might influence the participants' answer for the branch. Figure 22 [Bottom Right] shows the zoomed-in view for the branch, which branch size might be hardly seen or estimated due to the noise / points around the branch. As far as the VR application's current development and the experimental point cloud data, participants could not accurately estimate the branch diameter size.

5.2.4 Sweep Assessment

As noted in Section 2.6, a sweep is the curvature of the stem away from a straight line placed along inside edges of sweep (Section 2.6, Figure 10). Sweep assessment is proportional to the Small End Diameter (SED) of the length over which stem was assessed. When applying a sweep code, the assessment of length (for example 4 m) must be applicable for the entire length of the sweep code. For example, it must be possible to fit up to a 4 m log with SED/4 anywhere throughout an 'S' code (short – gentle sweep of SED/4 over any 4 m length). There are several different types of sweep in field assessment according to the stem condition. There were 2 sweeps used in the experiment: *Sweep1* and *Sweep2*. Field assessment results for *Sweep1* was K (kink – sharp change direction of the stem) while for *Sweep2* was S. During the experiment, participants would call whatever sweep structure they noticed near the green tag and their answers were recorded manually by the researcher.

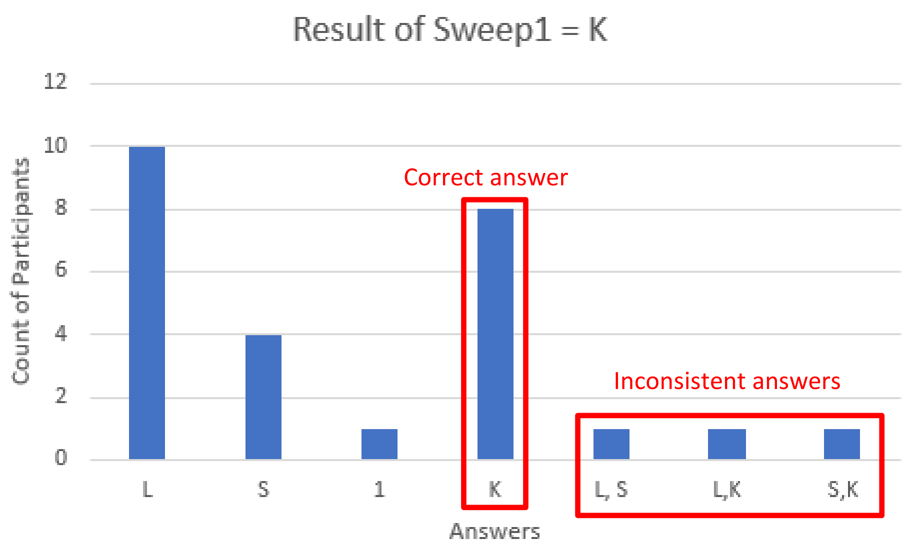


Figure 24: Participants' answers for *Sweep1* from the most straight sweep (L) to the least straight sweep (K), as well as other inconsistent answers.

As shown in Figure 24, there were eight out of twenty-six participants who answered correctly. Eighteen participants provided incorrect answers.

Ten participants answered L and four participants answered S. Both L and S are categorised as gentle sweep (Section 2.6). It depended on how participants divided the section according to SED size. Each participant had different visual estimation when estimating the SED size and there were no specific measurement tools to aid this estimation in the experiment.

There were three participants who provided inconsistent answers (more than one answer for *Sweep1*): 'L, S', 'L, K', and 'S, K'. It was possible that these happened due to two factors. First, there was no advice provided by the researcher during the experiment regarding how many sweep structures should be assessed. Second, the green tag located in the stem was placed at a location that could potentially cause misinterpretation by the participants. For example, when participants either did not see the K or chose one of L or S, and K. Figure 25 illustrates the evidence of the misplaced green tag.

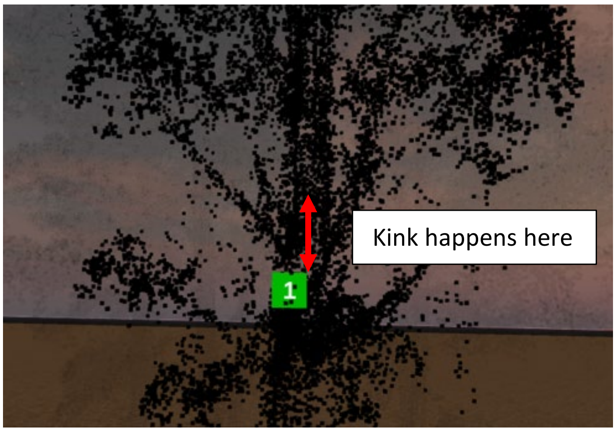


Figure 25: *Sweep1* (kink) was located right above the green tag.

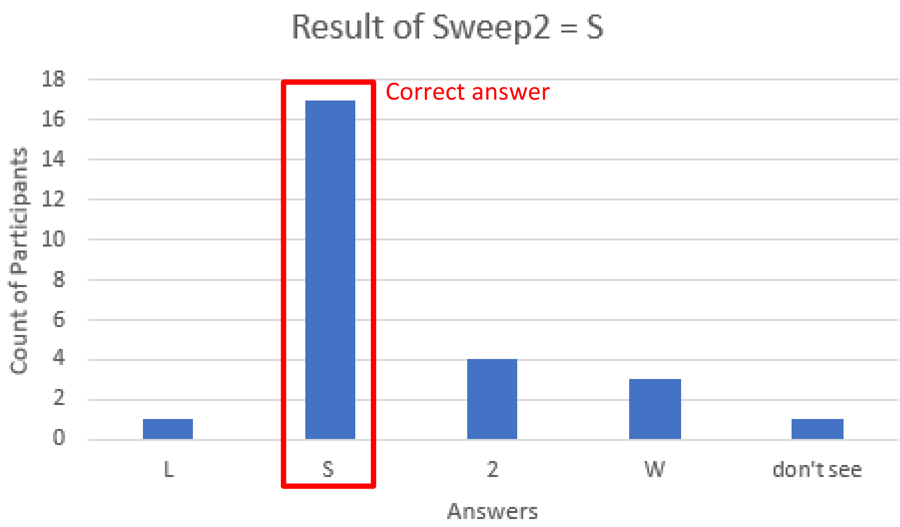


Figure 26: Participants' answers for *Sweep2* from the most straight sweep (L) to the least straight sweep (W), as well as other answer (don't see).

The correct answer for *Sweep2* was S. As shown in Figure 26, the majority of participants (17 participants) answered correctly. Nine participants provided incorrect answers.

One of the participants answered L, which was closely related to the correct answer because L and S are considered as gentle sweep. Figure 27 illustrates the *Sweep2*. It was a matter of how the participant estimated the SED size of *Sweep2* that made the stem curvature belongs to L or S.

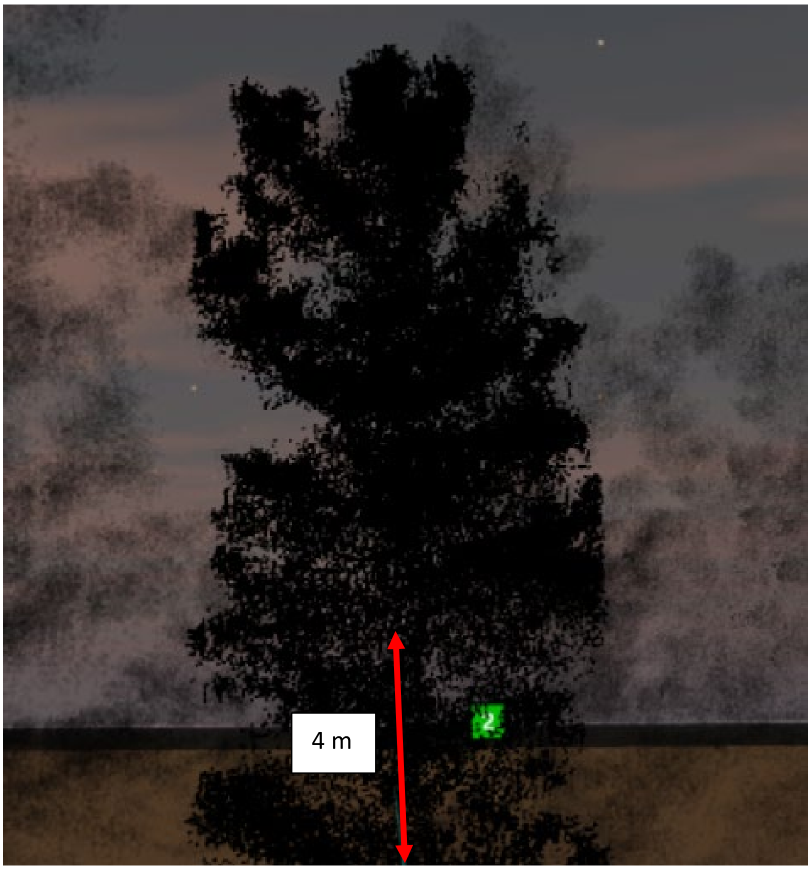


Figure 27: *Sweep2* in VR-point cloud. The green tag located the section for *Sweep2* (S – SED/4 for any 4 m length) that should be estimated by participants. Since the green tag was within 4 m log (shown in red arrow), the sweep structure of *Sweep2* was S.

There were four participants who answered ‘2’. Sweep ‘2’ belongs to moderate sweep. There is a slight difference between gentle and moderate sweep. Gentle sweep is SED/4 over any 4 m (or 6 m) length, while moderate sweep is SED/2 over any 3 m length. It depends on how those participants estimated the SED size.

There were three participants answered W (wobble – two or more deviations/sharp changes occur on the stem at > 5 cm length) and one participant who did not see any sweeps. This research could not find evidence to explain their performance.

5.2.5 Feature Assessment

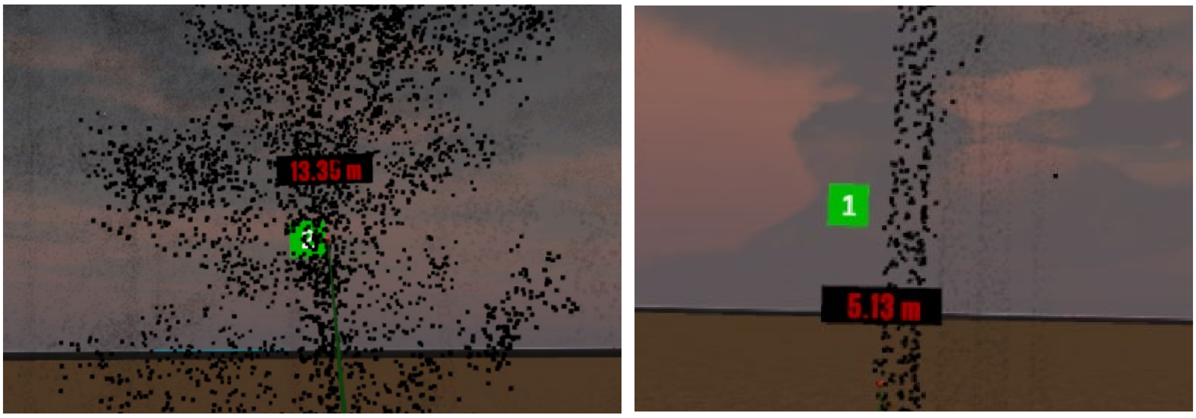


Figure 28: [Left] *Feature1* S10+ was located at 13.35 m height. [Right] *Feature2* damage was located at 5.13 m height. The green tags located the features that should be estimated by participants.

There were 26 participants for feature assessment. There are several codes for feature assessment according to the reference card outlined in Section 2.6. Each code represents a different type of structure that can form on a stem. These structures are considered anomalies from a perfectly formed tree (no additional structures on the tree e.g. scars or swelling stem). There were 2 features used for feature assessment as illustrated in Figure 28: *Feature1* and *Feature2*. Field assessment result for *Feature1* was S10+ (spike knot 10 cm) and *Feature2* was damage (indicating points of damage on the stem of the tree).

During the experiment, participants would call whatever features they noticed near the green tag and their answers were recorded manually by the researcher. The results are illustrated in Figure 29.

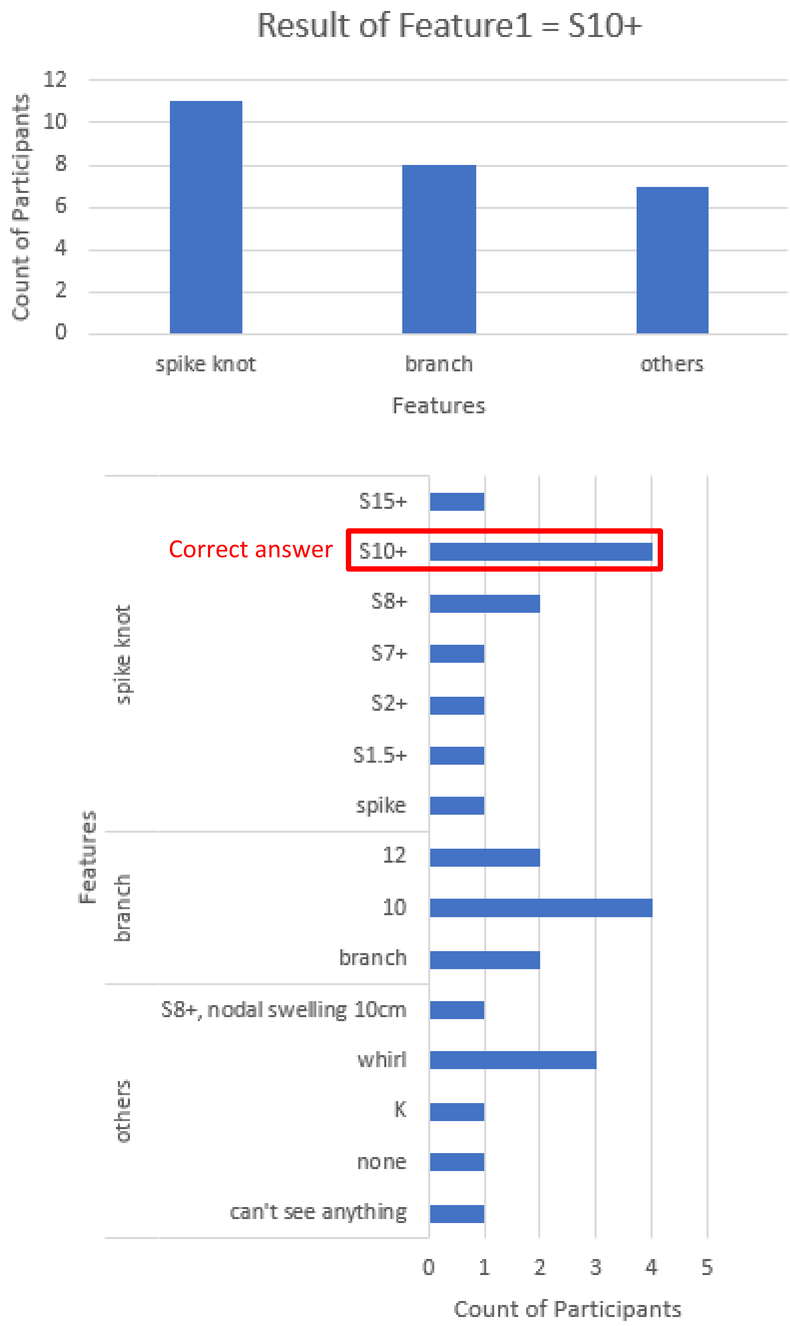


Figure 29: [Top] Participants' answers for *Feature1* grouped into spike knot, branch, and others (other answers). [Bottom] Details for each feature groups.

Feature1 (S10+) was a 10 cm spike knot – formed when a branch has grown at an acute angle to the stem of the tree, typically at the angle of less than 20 degrees to the stem. As shown in Figure 29 [Bottom], there were only four participants who answered correctly. Twenty-two participants provided incorrect answers.

There were eleven participants who answered spike knot with different sizes according to Figure 29 [Top], including those who provided correct answers. This means they could see that it was a spike knot. However, their perception in estimating the diameter size of the spike knot was not consistent or necessarily accurate.

Eight participants mistakenly assessed the spike knot as a normal branch, e.g. 10 or 12 (branch size of 10 or 12). Two of these participants could not estimate the branch size. The different key characteristic between a spike knot and a normal branch is the angle to the stem of the tree, where a spike knot has less than 20 degrees and a normal branch would have more than 20 degrees.

Some other answers were either 'can't see anything', 'none', or 'kink' – the latest is a sweep structure. These answers could probably be attributed to poor point cloud visualisation around the structure as shown as Figure 28 [Left]. The points were too sparse to view the structure, and therefore making visual estimation difficult.

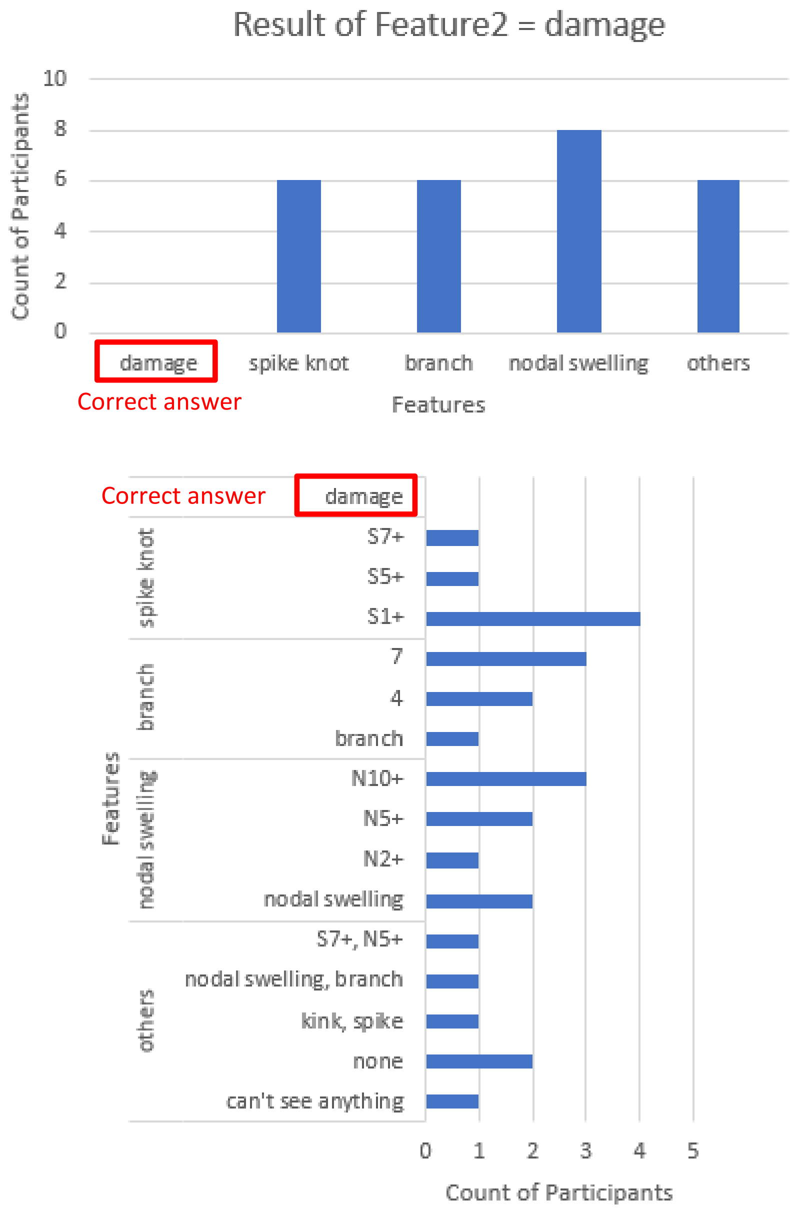


Figure 30: [Top] Participants' answers for *Feature2* grouped into damage, spike knot, branch, nodal swelling, and other answers. No correct answer. [Bottom] Details for each feature groups.

The correct answer for *Feature2* was damage. However, as seen in Figure 30 [Top], none of the participants answered correctly.

Considering that eight participants identified nodal swelling, the structure of the damage tree might appear in the point cloud to be similar to the nodal swelling condition. Nodal swelling is a swelling stem that occurs around a branch node. Damage is a damaged stem in the form of holes or scaring on the stem. Figure 31 [Left] illustrates the damage section (green tag is within the damage section). The assessment result indicated that none of the participants could see the damage condition. This might be due to the participants' perception of the region around the damaged area, for example they did not notice the holes/scaring, however, they noticed the area above the holes/scaring and they perceived that as swelling on the stem (as shown in Figure 31 [Right]).

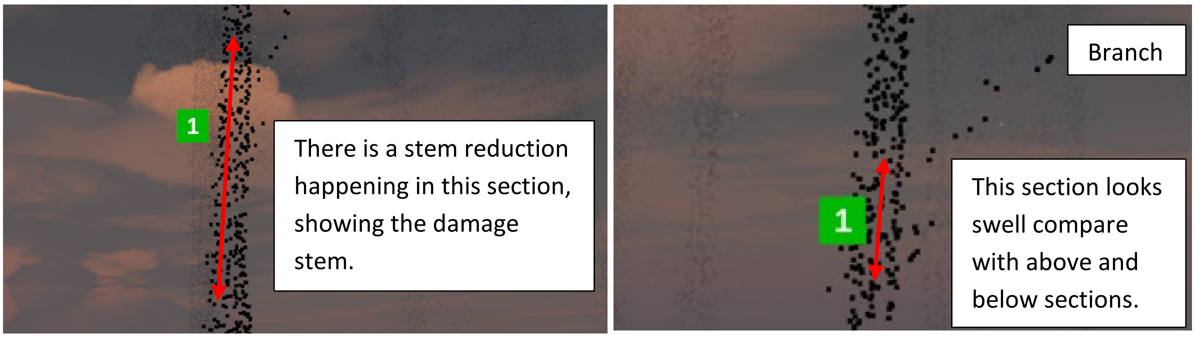


Figure 31: Damage stem viewed from two different positions. [Left] Section where the damage happened. [Right] Section that looked similar as nodal swelling.

Six participants answered branch with different sizes. This was probably because the damaged stem was located near a branch. Figure 31 [Right] illustrates this condition. Therefore, these participants could possibly focus more on the branch structure rather than damage structure.

Figure 32 shows the condition of spike knot and damage in the field plantation. From those conditions, it can be conceived that estimating features inside VR can be a challenge. For the spike knot, as noticed from Figure 29 there were other assessment errors other than the difficulty in estimating the size of the spike, such as when participants incorrectly estimated as a normal branch. For the damage, point cloud visualisation should provide colour and more points to the damaged structure to distinguish any damages on the stem.

Figure 32: Both pictures were from the field plantation. Copyright 2020 by Interpine Group Ltd. [Left] Red tape was a height pole showing the height of the spike (1.4 m to 1.6 m); Red curve showed a spike with a 10+ (11-16 cm) branch. [Right] Red circles marked two severe stem damage conditions.

5.3 Results and Analyses of Practitioners' Feedback

This section describes the results and analyses of practitioners' feedback about their experience of using the VR-point cloud for individual tree assessments. The analyses were drawn from post-experiment feedback about tree assessments in VR (five assessments), feedback about consistency with real world assessment, and feedback about the adoption of VR-point cloud to replace field-based data collection. There were two types of feedback from the questionnaire: Likert scale and open-ended written feedback.

5.3.1 Feedback about tree assessments in VR

Analysis of this feedback was drawn from the Likert scale and coding from the questionnaire in post-experiment. The feedback was measured based on participants who completed each assessment so that the analysis result of the feedback was aligned with each assessment's task performance. There were five assessments: height, diameter, branch, sweep, and feature. The Likert scale percentage is shown in Table 9 and the coding of the open-ended written feedback is shown in Table 10. The coding process was described in Section 4.4.

Table 9: Likert scale percentage from each assessment.

Questionnaire statements	**No. of Participants**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
It is easy to estimate *height* of trees.	26	46%	42%	12%	0%	0%
It is easy to measure the stem *diameter* of individual trees.	24	8%	33%	46%	8%	5%
It is easy to measure the *branch* size of individual branch.	14	0%	7%	14%	65%	14%
It is easy to determine *sweep* of individual branch.	26	8%	38%	35%	15%	4%
It is easy to determine *features* of individual trees.	26	4%	16%	40%	40%	0%

Table 10: Coding from open-ended written feedback about assessments. Following the questionnaire statements in Table 9, participants were asked to provide written feedback if there were difficulties in each assessment. The original question following each questionnaire statement was: *if there are difficulties, please detail them below*. Refer to Appendix C for the questionnaire form.

Assessments	**Final coding**	**Initial coding**	**Written feedback (Questionnaire)**
Height assessment	• Lost in the canopy when elevating to the top • Height assessment is very easy • First time VR users need practice in using height tool	• Lost in the canopy when elevating to the top • Height assessment is very easy • First time VR users need practice in using height tool	Very easy, the tool was handy.
			When moving up to the top of the tree, I found I became lost a bit when other trees were close by and wasn't sure which was the right tree.
			Not hard at all, just a matter of familiarizing and getting used to the controllers.
			Sometimes not sure if you are seeing to top of the correct tree once you fly into the canopy.
			I found this quite hard as a first-time user.
Diameter assessment	• Diameter assessment is challenging • No confidence in assessment accuracy • Tools sometimes unstable and difficult to use	• Diameter assessment is challenging • Tools sometimes unstable and difficult to use • No depth perspective • Missing pixels • No confidence in assessment accuracy • Need more practice of the tools	It is fairly easy to measure the diameter of the stems although I found the lasso tool quite glitchy / touchy.
			I would be concerned about the accuracy of the measurement.
			Had to edit a few times, was hard to get the diameter perfect.
			The diameter tool was not easy to use, required various adjustments to ensure the accuracy, and even then I did not feel confident of measurement.
			No depth perspective, tree edges are not well defined, tools is not easy to manipulate precisely.
			I found hard to adjust the size of the circle, and in the case of missing pixels I probably underestimated the diameter.
			Did take a little time to get used to it but with more practice it would only get easier.
			It can be done precisely but you need to view the tree from multiple angles.
Branch assessment	• Difficulty in identifying branch • Few points around branch (not dense enough) • Unable to determine branch size	• Difficulty in identifying branch • Few points around branch (not dense enough) • Unable to determine branch size • Challenging assessment	Although the point cloud is high density, it is not quite fine enough to easily, accurately, and confidently assess branch size.
			Hard to identify branching when they are points.
			I had a hard time trying to distinguish branch size.
			Points not enough to illustrate branch sizing. There were too few

			points in the branching to make a good measurement.
			I found it difficult to assess branching.
Sweep assessment	• Difficulty in estimating sweep around the canopy • Severe or obvious sweeps are easy to see • Sweep assessment is easy but sometimes challenging around the canopy	• Difficulty in estimating sweep around the canopy • Severe or obvious sweeps are easy to see • Sweep assessment is easy but sometimes challenging around the canopy	Easy to see sweep with no canopy, but where heavy canopy was difficult.
			Easy to see the really bad sweeps (kink, 1, or X) but not the minor ones.
			It is more difficult up in canopy where there are more branches / dots making it harder to see stem. Lower part of three is easier to see sweep because less branches / dots.
Feature assessment	• Feature assessment is difficult • Features are vague and not clear at canopy • Obvious features (spike knots on bigger branches, forks, and nodal swelling) are easy to identify • Not enough points to identify features	• Feature assessment is difficult • Features are vague and not clear at canopy • Obvious features (spike knots on bigger branches, forks, and nodal swelling) are easy to identify • Not enough points to identify features	Spikes were pretty easy, nodal a bit subjective. Forks are easy to see.
			Major / obvious features e.g. forks would be easy to identify, but minor / less obvious features e.g. spikes, small kinks would be difficult to identify without a higher density point cloud.
			Features like nodal swelling and forks can be easily determined.
			I personally had a hard time trying to determine features.
			Opportunity for guess work, illustrated features were vague and needed a more detailed point cloud.
			Spikes were easy on bigger branches due to more dots, but smaller branches more difficult to identify spikes.
			Some features had enough points to be easily discerned. Still uncertain if lack of the features is due to no feature or just no points struck.

Most participants either strongly agreed (46%) or agreed (42%) that height assessment was easy, as shown by the Likert scale (Table 9). None of the participants selected *'disagree'* or *'strongly disagree'* for ease-of-use of height assessment. Coding from written feedback also indicated that height assessment was easy, although some participants had lost sense of direction in the canopy when elevating to the top. According to the coding result, height tool was not hard to use, however practice was needed for first time VR users. One of the participants wrote: *"not hard at all is just a matter of familiarising to the controllers"*. Based on the Likert scale questionnaires' results and written feedback, participants found that height assessment in VR-point cloud were simple to perform.

Diameter assessment was challenging according to the coding analysis. Likert scale analysis indicated that most participants selected either *'agree'* (33%) or *'neutral'* (46%) for ease-of-use of diameter assessment. This result could be attributed to a circle tool used for diameter assessment. Some participants mentioned that the circle tool was sometimes unstable and difficult to use; for instance "*had to edit [a] few times, was hard to get the diameter perfect*", "*the diameter tool was not easy to use,* *required various adjustments to ensure the accuracy, and even [then] I did not feel confident of measurement*", and "*no depth perspective, tree edges are not well defined, tools [are] not easy to manipulate precisely*". As reflected from those comments, not only the circle tool but also structure of the point cloud data around diameter area made it difficult to get the diameter perfect, e.g. tree edges were not well defined. If diameter assessment was considered in VR, there should be improvement from both sides: the circle tool and the structure around the edges of the diameter (e.g. the point cloud density).

Similar to the diameter assessment, branch assessment was also considered to be challenging. According to the Likert scale, 79% of the participants selected '*disagree*' or '*strongly disagree*' for ease-of-use of branch assessment. These results were reflected in the written feedback. As shown in Table 10, three themes emerged from the written feedback: *'difficulty in identifying branch'*, *'unable to determine branch size'*, and *'not enough points for branch'*. These themes were related to one another. The difficulty in identifying the branch might be due to not enough points around branch structures, and therefore it was hard to estimate branch size. The Likert scale questionnaire and the written feedback indicated that branch assessment was difficult in the VR-point cloud environment since the branch structures were difficult to identify. Some possible improvements might include improvement from the point cloud visualisation (e.g. higher LiDAR point density would be needed for the branch structures) and improvement from a branch tool to enable accurate branch diameter size estimation.

For sweep assessment, a majority of responses to Likert scale selected '*agree*' (38%) or '*neutral*' (35%) for ease-of-use of the assessment. However, 15% of participants disagreed that sweep was easy and 4% strongly disagreed. The results from the Likert scale responses were reflected in written feedback shown as Table 10. Interestingly, the written feedback was not only participants' opinion about sweep structures that were shown during the experiment but also participants' perspective of other sweep structures that might or might not be visible in VR-point cloud. According to the written feedback, some *obvious* sweep structures (such as kink) or other structures that located below the canopy were easy to identify. However, some sweep structures that were located at the vicinity of the canopy area were difficult to identify. This result shows a possibility of sweep assessment in a VR-point cloud. There might be risks of having inaccurate assessment around the canopy area, depending on the structure of the sweep and the density of vegetation in the canopy area.

Feature assessment comprised different structures of anomaly located at the stem. The Likert scale results showed that most participants were either *'neutral'* (40%) or *'disagree'* (40%) that feature assessment was easy. Like sweep assessment, features presented in the experiment and other features based on participants' perspective about possible visible features in VR-point cloud were mentioned in the written feedback. According to the written feedback, some *obvious* features such as spike knots, forks (two-branched stem), and nodal swelling could be easy to identify. Other features could be hard to identify because these features in VR-point cloud were not well defined and needed a more detailed point cloud visualisation. Features located in canopy vicinity were also difficult to see because the number of LiDAR strikes on the stem was lower in the vicinity of the canopy, presumably because the vegetation in the canopy was reducing stem strikes.

5.3.2 Feedback about consistency with real world assessment

Feedback about consistency with real world assessment might define the similarity of experience in a VR-point cloud environment when compared with experience in a field. Suppose the experience in a VR-point cloud environment was consistent with a real-world experience. In that case, there is likely to be a higher possibility of field assessment skills being brought into VR. Analysis of this feedback was drawn from Likert scale responses and coding from the questionnaire in the experiment. The result of the Likert scale and coding are shown in Table 11 and Table 12 respectively.

Table 11: Likert scale percentage from *'consistency with real world assessment'*. There were 31 participants responded to this Likert scale.

Questionnaire statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
My experience in the VR forest seems consistent with experience being in a real forest.	6%	45%	23%	23%	3%

Table 12: Steps in coding from *'consistency with real world assessment'* open-ended written feedback. Following the questionnaire statement in Table 11, participants were asked to provide written feedback of their experience based on their Likert scale responses. The original statement following the questionnaire statement was: *Please explain your experience*. Refer to Appendix C for the questionnaire form.

Final coding	Initial coding	Written feedback (Questionnaire)
Similarity and consistency with real world	• Similarity with real world • Consistency with real world • VR experience is better than experience in a real forest	Very good experience, better than being in the actual forest.
		It felt like I was in a real plot. More detail would increase that experience. I did like the sunset sky in the background.
		Trees and spacing, shapes of tree and other undergrowth were very realistic.
		You can do the same that we do in the forest, tag, height, diameter.
		Lots of similarity though in the forest structure and in cruising method required i.e. moving around to get best view of trees and features.
		Being in the VR forest was not hugely dissimilar from being in the real forest.
		Could see stems easy and walk around trees.
		An excellent experience. Almost like real thing, Leads of potential.
		It was far better than being in a forest – dry / warm.
		It feels more like physically standing there in the plot (bush) and cruising the trees. This VR is so amazing that it even allows you to look closer at the trees you're cruising, especially close to the top where it's hard to see features as in ordinary plotting.

Contradictions of point cloud in VR	• Negative notions of point cloud in VR • Reasons for negative notions of point cloud in VR • Improvement in terms of visualisation is required for VR-point cloud	I couldn't quite see the tree fully to estimate what codes were on theirs as I would in a real forest.
		Easier to visualise tree features in a real forest but probably it would be easier and more accurate to measure features in a VR forest if had better point cloud data.
		The issue (seemed from point cloud) was the lack of detail or resolution of the branch – branch to the stem and the upper stem. Perhaps colouring the stem pixels and branch and foliage differently might help.
		The point cloud doesn't have enough clarity to compare to reality. Missing colour variations e.g. brown branches and trunks, green canopy.
		The canopy is not easy to distinguish individual trees.
		We need to work with images as well to see for example dead trees.
		Totally different environments. I did find the VR quite disorienting and a bit nauseating.

It was hard to say that participants' experience in a VR-point cloud environment was consistent with real world (forest) experience from Likert scale resulting percentage. The Likert scale showed that more than half of the participants responded with *'agree'* (45%) or *'neutral'* (23%) to a statement that their experience in the VR seemed consistent with the experience of being in a real forest. 26% of participants from the Likert scale responded with *'disagree'* (23%) or *'strongly disagree'* (3%) that their VR experience is consistent with the real forest.

In analysing 'consistency with real world assessment' feedback, there were two themes emerged from the final coding. The two themes were: '*similarity and consistency with the real world*' and '*contradictions of point cloud in VR*'. Some participants wrote that their experience in a VR environment was similar with their experience in a real forest in terms of presence and ability to perform the assessments. Other participants mentioned that VR environment was better than real forest because they could easily walk around the environment and see/inspect structures closer than in a real forest. Another theme was about contradictions of point cloud in VR. The issues mostly lied on the lack of details in point cloud visualisation, such as could not see the structures clearly around canopy areas due to the absence of colour point data or could not see features such as dead trees (damage stem). The former could also be due to the lack of points in certain areas such as branches. The latter seemed to stem from point cloud inability to present damage structures (point cloud was not the best way to present these structures). One of the participants wrote this as "*I couldn't quite see the tree [structures] fully [in VR-point cloud] to estimate what codes were on ~~theirs~~ [the stems] as [compared to estimating structures] ~~I would~~ in a real forest.*". The trees in VR-point cloud were not realistic as in the real forest since they comprised point cloud forming a tree-like structure and there was no colour attached to the points. Another participant found that the VR environment was disorienting and nauseating, so VR experience was inconsistent with their experience of a real forest.

5.3.3 Feedback about the adoption of VR-point cloud to replace field-based data collection

Feedback about the adoption of VR-point cloud to replace field-based data collection might indicate whether VR environment could replace field assessment in terms of individual radiata pine tree assessment. Analysis of this feedback was drawn from Likert scale responses and coding from the questionnaire in the experiment. The result of the Likert scale and coding are shown in Table 13 and Table 14 respectively.

Table 13: Likert scale percentage from *'the adoption of VR-point cloud to replace field-based data collection'*. Only 23 participants responded to this Likert scale.

Questionnaire statement	Within 1 year	Next 1-3 years	Not in the near future
How long [before] ~~do~~ you think this VR technology can be adopted into the practical forest *cruising*?	17%	66%	17%

Table 14: Steps in coding from *'the adoption of VR-point cloud to replace field-based data collection'* open-ended written feedback. Following the questionnaire statement in Table 13, participants were asked to provide written feedback about the adoption of VR-point cloud to replace field-based data collection based on their Likert scale responses. The original statement following the questionnaire statement was: *Please provide explanation*. Refer to Appendix C for the questionnaire form.

Final coding	Initial coding	Written feedback (Questionnaire)
Confidence of VR technology adoption to practical forest *cruising*	• The development of VR-point cloud technology for forest industry • Confidence of VR technology adoption to practical forest cruising in the near future	If I can pick up the basics of use within an hour of been shown, it can be used definitely in the near future. A VR-controlled logging equipment may safe life in the future.
		It's already amazing at this stage and I reckon with all constructive comments from feedbacks it would certainly help the makers improve this VR technology within the next one to three years.
		With some improvements especially simplification of the joysticks we should see it being used in the future.
		With well-trained operators it could be used shortly.
		In the end, anything is possible, it's just how much resource to allocate to achieve it. As scanning technology improves so will the dataset. It is inevitable that through human learning, machine learning will in the end be the result.
Uncertainty of VR technology adoption to practical forest *cruising*	• Uncertainty of the timeline for VR technology adoption to practical forest *cruising*	Very close, but not quite there in my honest opinion.
		Still needs some work, but maybe 50% there.

	• Difficulties in applying VR for forest industry	Require major changes in people, organisations, workflow, IT infrastructure. These will take time.
		VR will need to be improved to produce higher density point cloud data and more accurate measurement than traditional field measurement. This will also depend on the economic variables at play in the industry. If it doesn't make dollars, it doesn't make sense.
		To do this would require some pretty sophisticated machine learning although I'm not sure that the algorithm would cruise as a human would.
		The technology is getting there but we need to work on how to put a better dataset into VR.

There were two themes that emerged from the coding as shown from Table 14: confidence and uncertainty of VR technology adoption to practical forest *cruising*. Some participants were optimistic that technology such as VR or point cloud visualisation could be improved in the near future. This was reflected in the Likert scale shown in Table 13 that most participants (83%) agreed that VR could be adopted into practical forest *cruising* in the near future (17% within 1 year and 66% within 1-3 years). Currently, VR-point cloud assessments need more works in terms of improving the measurement tools and improving the point cloud visualisation in the VR environment. On the other hand, 17% of participants expected that VR could not be adopted to practical forest *cruising* in the near future. VR was assessed as not yet ready for individual tree assessment and needed further development to provide accurate assessment similar to the current practice. There were many difficulties in applying VR to the forest industry and there was an uncertainty of the timeline for the VR technology to be adopted for the forest industry.

Chapter 6 Discussion

6.1 Discussion

As discussed in Section 2.7, VR (Virtual Reality) as a visualisation platform can accommodate visualisation of a very large number of data points. This could potentially be helpful in providing a virtual environment for structural estimation tasks in individual tree assessment, such as for radiata pine trees as outlined in this research. There are different structures that require documentation and measurement in individual tree assessments for radiata pine (Section 2.6): height, diameter, branch, sweep, and feature. Incorporating these structures into inventory assessment using VR-point cloud data has resulted in different task performance outcomes compared with traditional field assessment. There are several key factors identified in this research that contribute to the performance differences.

i. *The type of tree structure*. In a field, the structure is a physically solid 3D tree. In a VR-point cloud, the structure is represented by a point cloud forming the 3D structure of an object which may make it difficult to estimate the structure type.
ii. *The method of data representation*. In this work, the remotely sensed forest data has been represented in the VR environment as raw data in the form of point clouds.
iii. *The tools and assessment mechanisms*. In this research, the tools refer to measurement tools that were used to assess the tree in a VR-point cloud.
iv. *Other human factors that varied between participants*. This research has identified some evidence of human factors that affect performance in the VR-point cloud.

The first factor is related with the structure type which is represented by the point cloud data. As identified from this research, point cloud did not clearly present some structures for three reasons. Firstly, the low density of the point cloud, such as branches at lower canopy areas, resulted in sparse points for the branch structures. Secondly, the complex and noisy areas, such as the canopy, which contain a dense region of points to see the stem structure. Thirdly, the non-solid structures, such as at the outer bark of the stem, which make it difficult to estimate the tree diameter.

Structural estimation of the curvature of a stem (sweep assessment) was in most cases successfully accomplished by participants in the VR-point cloud environment. Most participants reported that they found sweep assessment easy to do in VR-point cloud. Although there were some incorrect answers, most of these answers identified categories that were structurally very close to the correct answers.

On the other hand, structures such as diameter, branch, and features were shown to be more difficult to estimate inside the VR-point cloud. For example, in feature assessment when estimating the S10+ structure and the damage structure as outlined in Figure 29 and Figure 30 respectively. There were only four out of twenty-six participants who could estimate these structure type and size correctly for S10+ structure and none of the participants answered correctly for damage structure. Coding results from the feature assessment shown as Table 10 indicated that there were not enough points to estimate the structures, therefore features in VR-point cloud could not be seen clearly. Structures such as stem damage are very likely to be difficult to see in a VR-point cloud unless the damage is severe (and so can very obviously be seen), even if the point cloud density is very high, or unless stem colour is captured and used to indicate the damage structure.

The second factor that contributes to the performance difference is the visualisation of the point cloud data. In the VR-point cloud, visualisation plays an essential part in achieving high reliability and accuracy. However, as noted earlier in this section, it was hard to estimate structures in certain areas due to the point cloud's structure type. For example, in the diameter assessment, there were sparse points around the outer bark of the stem in VR-point cloud as shown in Figure 18 [top]. This was probably due to fewer airborne LiDAR scan returns at points low in the canopy and close to the ground. As a result, the demerit calculation accuracy score was low because of the consistent difference between VR-point cloud assessment and field assessment across all participants. Another example is the branch and feature assessment, where participants' feedback has shown issues related with point cloud visualisation, such as *"not enough points for branch"* and *"features are vague and needed a more detailed point cloud visualisation"*. Diameter and branch structures require more points at the assessed area(s) to enable accurate estimation. This could be improved if there were a higher rate of LiDAR scan returns. Features require targeted visualisation such as displaying different colours on the stem if there are any features on that assessed location, so that those features can be more easily noticed in VR-point cloud. Displaying different colours for the stem and leaves might also help in accuracy improvement for structures around the canopy areas.

Some participants mentioned that they could not really see the stem structure (sweep assessment) around the canopy areas due to more branches or too dense points. Displaying different colours on the stem and branches or providing transparent visualisation to the branches/leaves while selecting the stem might help to make the stem structure clearer. However, this would only be possible when LiDAR points exist inside the canopy. The colour segmentation process could involve machine learning approaches to segment sections between stem and leaves (Windrim and Bryson, 2018). If applicable, the colour segmentation process could be defined based on the distance of the participant to the tree(s). For example, using a darker colour for some leaves at certain areas to indicate the depth and distance of the tree(s) to the participant's position. This would be helpful for height assessment in the VR-point cloud, where participants lost their sense of directions when elevating to the top. Another alternative for visualisation improvement in the VR-point cloud is to experiment with a surface model such as mesh derived from the point cloud. The surface model derived from the point cloud, however, could potentially contain artefacts and errors.

The third factor that contributes to the performance difference is assessment mechanism in VR. For example, the use of a height tool and a circle tool required for height and diameter assessments respectively. The tools should aim to assist participants in structural assessment in the VR-point cloud. In the case of height assessment in the field, it is often difficult to assess tree height because it is not possible to get a clear view of the top of a tree. In the case of height assessment in a VR-point cloud, the height tool is helpful because it allows the participants to elevate to the top of the tree (using joystick navigation) and observe the highest point in the point cloud. The assessment accuracy, however, not only depends on the mechanism of the height tool but also on the point cloud visualisation. In diameter assessment, some participants mentioned that the circle tool was sometimes unstable and difficult to use, such as *"the diameter tool was not easy to use, required various adjustments [when creating the lasso] to ensure the accuracy, and even [then] I did not feel confident of measurement [accuracy]"* and *"had to edit [the lasso] a few times, was hard to get the diameter perfect"*. Some difficulties using the circle tool could affect accuracy of diameter assessment. Previous work by (Chen et al., 2019) can be considered to improve the lasso selection technique with the assistance of deep learning in selecting subsets of 3D point cloud datasets, especially for diameter and branch assessment (when estimating the branch diameter size). Furthermore, the improved lasso selection technique can be combined with VR sensory feedback, e.g. auditory or haptic feedback, to indicate whether the desired lasso size has been achieved. However, this would require sufficient datasets for the deep learning. For example, datasets of some lassos that cover all points at the outer bark of the stem at 1.3 m (the required height for diameter). There should be a threshold for these lassos to be considered as 'acceptable' datasets for the deep learning techniques. Tolerance allowance can be considered as the maximum threshold value so that the lassos will not incur demerit.

The last, and probably the most crucial factor affecting the performance difference is the human factor. This research revealed evidence of human factor that influence height and diameter assessment results. In height assessment, the evidence is shown in Figure 17 where there are several selected points at the peak of the tree as results of individual participant's decision in choosing the point cloud data at the peak of the tree. Figure 21 shows evidence of human factor in the diameter assessment where there are different sizes of circles as results of participants' different visual estimation when assessing the structure around the required height for diameter. There are many other human factors that have not been explored further in this research, such as whether participants' position in inspecting the structures in VR-point cloud could have affected task performance. VR is known to provide an immersive environment that can help humans perceive and comprehend the structure of point cloud data (Prouzeau et al., 2019). Further investigation of human factors is required, especially when implementing VR-point cloud assessment in domains that have different knowledge and expertise required for the assessment.

VR has shown a positive result in providing virtual environments for individual tree assessment of radiata pine trees. The results and analyses of this research have shown that the participants could perform assessments in a VR-point cloud, regardless of their experience with VR and how they rated the measurement tools used for the experiment. However, their performance was not always accurate as they were affected by the factors described above.

In terms of radiata pine tree assessment in a VR-point cloud, some participants indicated that their experience of doing the assessment in VR-point cloud was not consistent with their experience of doing assessment in a field. The VR-point cloud could provide easier exploration (such as navigating or walking around the virtual environment) as compared with walking around in the field where there are many obstacles such as weather and terrain condition. However, not being able to see the trees in their real structure (e.g. solid 3D structure of stems and leaves, with different colours on stems and leaves) in VR makes their experience inconsistent with the real world and could make their assessments in VR-point cloud less accurate than in the field.

According to participants in this research, height and sweep assessments in the VR-point cloud are expected to be implemented sooner (within 1-3 years) as compared to diameter, branch, and features assessments. This is due to the difficulty of structural estimation of the diameter, branch, and features assessments in VR-point cloud. If the improvement of VR-point cloud interaction techniques (e.g. measurement tools for individual tree assessment) were aligned with improvement in the data acquisition (e.g. improved data from the LiDAR scan return), then VR technology might be adopted for forestry sooner than expected. Some participants argued for the use of machine learning instead of human structural estimation in VR-point cloud. In terms of individual tree assessment where there are several structural types such as for sweep and feature assessment, machine learning estimation might struggle to surpass human recognition of those structures because deep learning requires various training data to learn the different structures. As long as the training data is adequate, assessment with machine learning should be applicable. By the time the machine learning assessment is applicable, human role might be needed only to audit or validate the machine learning estimation. The machine learning assessment and the human validation in VR-point cloud (from machine learning assessment) can be developed alongside each other over the coming years to deal with the challenging complex forest structure visualisation.

6.2 Limitations

There are three limitations highlighted from this research as follows:

- This research focuses on individual radiata pine tree assessment with only one dataset provided only from Interpine company because the project is funded by Interpine company. Additional experiments with multiple datasets collected from the same forest types or forest conditions are required in order to test the robustness of the findings reported here.
- While human perception, cognition, and behaviour may contribute significant differences in the task performance in VR-point cloud, this research does not include suitable measures to capture these attributes.
- This research does not analyse participants' feedback about the use of the navigation tools, such as joystick navigation and teleport, and the use of branch tool. This is because the feedback data was not sufficient for analysis as there were only few participants who provided feedback on the navigation tools and the branch tool. If there were sufficient number of participants, this could be an interesting future research in analysing the use of the navigation tools and VR tools for VR-point cloud to advise future researchers about the tools performance and suggest how best to improve the tools performance for VR-point cloud.

Chapter 7 Conclusion and Future Directions

This research compares the performance of individual radiata pine tree assessment in a VR-point clouds and in a field. The tasks comprised five inventory assessments of individual radiata pine trees. Incorporating practitioners into an experiment has a positive result in ensuring feedback from users with forest inventory experience, such as feedback about possible visible and non-visible structures in VR-point cloud. The practitioners showed that they were able to perform assessment in VR-point cloud using VR devices provided in the experiment, although their performance was not always accurate in some assessments due to several factors listed in Section 6.1.

There are four key findings from this research:

- Height assessment has the highest accuracy (from demerit calculation) compared with other assessments, e.g. diameter assessment, branch assessment, sweep assessment, or feature assessment.
- Factors that could affect task performance accuracy in VR-point clouds include the structure type (e.g. sparse points on branch structures), the point cloud visualisation in VR (e.g. no colour segmentation between stems and leaves), the assessment mechanism in VR (e.g. challenges when creating a lasso in diameter assessment), and the human factor (e.g. subjective decision in choosing the highest point in height assessment).
- Participants' responses indicate mixed opinions about the VR-point cloud's consistency with the real world. There are similarity and consistency between the VR-point cloud environment and the real forest according to the participants. However, there are negative notions about point cloud in VR. The point cloud in VR requires some improvements in terms of point cloud visualisation (e.g. displaying different colours on the point cloud).
- Participants responses indicate mixed opinions about the future adoption of VR-point clouds to replace field-based data collection. There is confidence about the fast development of VR technology and its capacity to be adopted in some ways within the forest industry in the near future. However, there is uncertainty about the timeline for adoption of VR technology into practical forest *cruising* due to external factors that should be addressed first before the adoption, such as improvement of LiDAR scan return and external resources required for VR application development (e.g. major changes in organisations and IT infrastructure).

VR-point cloud assessment depends on visualisation and interaction techniques to achieve accurate assessment. This research shows that point cloud visualisation issues are related to the structure type, such as the sparse points in the branch structures (due to not enough points in visualisation) or the noise at the canopy areas (due to no colour segmentation between stems and leaves). Some structures need more points to identify the structure type and the structure size, such as diameter of the stems and branches. Some structures comprised too many points especially in areas around the canopy. For structures that require more points or contain non-solid structures, improvements can be made to the LiDAR scan return, e.g. using multiple overlapped scanning path of the scanner (UAV overlapped flight pattern) to accommodate possible missing structures. For structures that comprised too many points, further research can investigate whether using different segmentation techniques on the point cloud visualisation could improve the accuracy of the assessments. As for the interaction techniques, improvements can be made by simplifying the mechanism of the measurement tools when interacting with the points. The mechanism should be designed as simple as practicable so that practitioners can focus more on the assessment instead of the use of the measurement tools.

Some improvements can be made to make the human experience in the VR-point cloud more consistent with the real world. These improvements may take several years, depending on the point cloud visualisation and VR interaction techniques. There was no negative response from participants regarding the hardware performance (e.g. Alienware 17 R4 laptop) and the VR devices used during the experiment from this research. Depending on the improvements (e.g. whether the point cloud requires advanced visualisation techniques), some VR applications may require high specification for the hardware.

Achieving a higher density of points in certain areas in a VR-point cloud (e.g. for diameter or branch assessment) is likely to be sufficient to improve task performance in the VR-point cloud. Incorporating machine learning estimation might be another option to assist structural estimation for height, diameter, and branch assessment. Some structures such as in sweep and features assessments may need more works in machine learning estimation. Assessments in VR-point cloud are likely to require human input for some time to come, to at least validate or audit machine learning estimation. Further research and development of human visualisation, interpretation, and measurement tools in a VR environment in order to support forest inventory are warranted.

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Appendix A – Consent Form

UNIVERSITY of TASMANIA | *Participant Consent Form v1.0 8/08/2018*

Virtual Reality with Forest Point Cloud Data

Participant Consent Form

1. I agree to take part in the research study named above.
2. I have read and understood the Information Sheet for this study.
3. The nature of the study has been explained to me.
4. I understand that the study involves exploring forest data using virtual reality interface. The whole study will take an approximate of 1.5 hours.
5. I understand that I should not participate if I have been diagnosed with vertigo.
6. I understand that participation involves the risk(s) of being in a Virtual Reality environment such as feelings of discomfort, disorientation, dizziness, or motion sickness. I am also informed that these risks have been mitigated in the design of this experiment.
7. I can confirm that I have no medical reason to self-exclude from the experiment.
8. I understand that I can choose to stop the experiment at any time during the experiment.
9. I understand that all research data will be stripped of personal identifiers and securely stored on the University of Tasmania premises for five years from the publication of the study results, and will then be destroyed.
10. Any questions that I have asked had been answered to my satisfaction.
11. I understand that the researchers will maintain confidentiality and that any information I supply to the researchers will be used only for the purposes of the research.
12. I understand that the results of the study will be published and that participants will not be identifiable.
13. I understand that my participation is voluntary and that I may withdraw at any time.
14. I understand that I will not be able to withdraw my data after completing the experiment as the data has been collected anonymously and will not be able to be identified to remove.

Page 1 of 2

Participant's name: ____

Participant's signature: ____

Date: ____________________

Statement by Investigator

☐ I have explained the project and the implications of participation in it to this volunteer and I believe that the consent is informed and that he/she understands the implications of participation.

If the Investigator has not had an opportunity to talk to participants prior to them participating, the following must be ticked.

☐ The participant has received the Information Sheet where my details have been provided so participants have had the opportunity to contact me prior to consenting to participate in this project.

Investigator's name: ____

Investigator's signature: ____

Date: ____________________

Appendix B – Information Sheet

Virtual Reality with Forest Point Cloud Data

Information sheet

1. Invitation

You are invited to participate in a research study exploring a potential for forest field operators to perform tree assessment with forest point cloud data inside an immersive Virtual Reality (VR) environment.

The researchers involved in the study include Dr. Winyu Chinthammit who is a research leader at the Human Interface Technology Laboratory (HIT Lab) within the Discipline of ICT, School of Technology, Environments and Design, University of Tasmania and Elisabeth Adelia Widjojo, an ICT PhD student at the University of Tasmania.

This study is being conducted for two purposes: (1) the fulfilment of a Doctor of Philosophy degree by student researcher Elisabeth Adelia Widjojo, under the supervision of Dr. Winyu Chinthammit and (2) the fulfilment of milestone 2.3 "Pilot usability testing sessions" and 2.4 "Analyses of the usability testing results" of the project "Enhanced forest inventory practice using immersive visualisation and measurement of dense point cloud data" RT.112513, in which Dr. Winyu Chinthammit is a Lead Chief Investigator.

2. What is the purpose of this study?

The study aims to improve our understanding on (1) how forest field operators perform tree stem assessment with forest point cloud data with our proof-of-concept VR forest application and (2) what are the factors that effect the human task performances inside this VR environment.

3. Why have I been invited to participate?

You have been identified as being eligible to participate in this experiment because you have experiences in forest field operations, particularly in tree assessment for forest inventory.

Participation in this experiment is voluntary. It is completely up to you whether you wish to participate.

If you wish to withdraw from the experiment once it has started, you can do so at any time without having to give a reason.

4. **What will I be asked to do?**
You will be asked to perform a series of tasks including tree marking (tree numbering) and measurement (tree height and diameter) with our proof-of-concept VR application. The 3D VR environment is reconstructed from dense point cloud data, scanned from tree plots in the real forests.

You will be required to wear a head mounted display (VR goggle/headset) to engage with our VR forest application and VR tools (through two left/right hand controllers). At the end of the experiment, you will be asked to fill in a questionnaire to provide feedback on your experiences of using the VR application and your opinions of the potential use of the application.

5. **Are there any possible benefits from participation in this study?**
This study is a trial for future VR applications for forest inventory cruising. The VR cruising has potential to reduce the need for field-based inventory cruising, which would reduce risks in occupational health and safety and could potentially improve the accuracy of the tree measurements.

Participants in this study will gain knowledge and experience of using virtual reality technology for forest visualization, which has potential to influence the industry practice.

6. **Are there any possible risks from participation in this study?**
During the experiment, participants will be exposed to a virtual reality environment.

The experiment is set up to ensure the potential risks of discomfort, disorientation, dizziness, or motion sickness while wearing the head-mounted display headset is reduced to a minimum. Nevertheless, participants who have been diagnosed with vertigo, who are easily susceptible to motion sickness, already have similar medical conditions or simply are concerned about the risks of being in a virtual reality environment should not participate in this experiment.

During the experiment, participants may choose to stop at any time if they feel any signs of motion sickness or discomfort. In addition, during the experiment, the experiment conductor(s) will be monitoring participants for potential signs or symptoms of these risks and will immediately stop the experiment if they are detected.

7. **What if I change my mind during or after the study?**
You are free to withdraw at any time during the experiment without having to give a reason.

The data that has been collected from any participants who choose to leave the experiment will be deleted at the moment the participants inform the experiment conductors of their desire to withdraw from the study.

However, we will not be able to withdraw your data after the entire experiment (over a number of participants) has concluded, as your data has been collected anonymously and will not be able to be identified to remove.

8. What will happen to the information when this study is over?

Data will be retained for a period of 5 years after the publications of the research findings to allow time for others to repeat the study, challenge the results and for us to be able to re-examine our data in such circumstances. At the end of the five-year period, spreadsheets will be deleted and/or paper files will be shredded and disposed through a secure mechanism.

All electronic data will also be backed up to a UTAS server space accessible only by the research team as required by the UTAS data management policy.

9. How will the results of the study be published?

The results of this study will be published in conference papers, journal articles and PhD dissertation of Elisabeth Widjojo. Any participants can email the researchers to enquire about the results of the research. The data collected from you will not be identifiable in the publication of the results.

10. What if I have questions about this study?

If you have any questions relating to this study please contact:

- Chief Investigator: Dr. Winyu Chinthammit (Winyu.Chinthammit@utas.edu.au)
- Student Investigator: Elisabeth Adelia Widjojo (Elisabeth.Widjojo@utas.edu.au)

This study has been approved by the Tasmanian Social Sciences Human Research Ethics Committee. If you have concerns or complaints about the conduct of this study, please contact the Executive Officer of the HREC (Tasmania) Network on +61 3 6226 6254 or email human.ethics@utas.edu.au. The Executive Officer is the person nominated to receive complaints from research participants. Please quote ethics reference number **H0017576**.

This information sheet is for you the participant to keep as a reference for your involvement in this study. Your involvement in this study will be contingent on you signing a written consent form that will be retained with the other secure documents and data relating to this study.

Appendix C – Questionnaire

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Subject ID: _________

Virtual Reality with Forest Point Cloud Data

Questionnaire

Section 1: Pre Experiment Data Collection

1. Age: _______
2. Gender: Female / Male / Other

3. Do you any problems with your vision that can effect the clarity of your vision? Yes / No

   If Yes, please shortly describe the conditions:

4. Have you ever worn a Virtual Reality headset? Yes / No
5. If **YES**, how familiar would you say you are with virtual reality technology?

   Not very (used once or twice)

   Somewhat

   (used a number of times but not often)

   Very (used it veryoften)

6. Please indicate your expertise(s) in the forest inventory from the list below?

   a) Crew Leader
   b) 2IC (Second in charge)
   c) Auditor
   d) Consulting
   e) Others, please specify ______________________________

   And how many years of experience do you have in that expertise?

   ____

Sweep	
Feature	

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Section 2: Subjective feedback on the use of the VR tools

1. It is easy to ***navigate*** (move around –including physical body movement, controller joysticks and teleportation) inside the VR forest.

   Strongly disagree   *Disagree*   *Neutral*   *Agree*   *Strongly agree*

   If there are difficulties, please detail them below:

2. I found the ***elevation tool*** (fly up and down) is very useful.

   Strongly disagree   *Disagree*   *Neutral*   *Agree*   *Strongly agree*

   Please explain how you used it:

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Section 3: Subjective feedback on the use of VR Cruising tasks

1. It is easy to ***measure the height*** of individual trees.

Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*

   If there are difficulties, please detail them below:

2. It is easy to ***measure the stem diameter*** of individual trees.

Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*

   If there are difficulties, please detail them below:

3. It is easy to ***measure the branch size*** of individual branch.

Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*

If there are difficulties, please detail them below:

4. (if applicable) It is easy to determine ***Sweep*** of individual branch.

Strongly disagree	*Disagree*	*Neutral*	*Agree*	*Strongly agree*

If there are difficulties, please detail them below:

5. (if applicable) It is easy to determine ***Features*** of individual trees.

Strongly disagree   *Disagree*   *Neutral*   *Agree*   *Strongly agree*

If there are difficulties, please detail them below:

Section 4: Other feedback

1. My experience in the VR forest seem consistent with experience being in a real forest.

Strongly disagree   *Disagree*   *Neutral*   *Agree*   *Strongly agree*

Please explain your experience:

2. How long do you think this VR technology can be adopted into the practical forest cruising?

Within 1 year / Next 1- 3 years / Not in the near future

Please provide explanation: